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Design and analysis of interactive video networks and servers

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Dedicated to the memory

of my Father,

who continues, every day,

to show me the way.

Abstract

Interactive video systems will form the basis of a vast range of new telecommunications services set to emerge in the coming years. Interactive video services enable the user to select and control the playback of video objects located on a remote server, in real-time. Telecommunications, storage and compression technologies are maturing and converging rapidly to make interactive video achievable in the wide area. These interactive video services will transform information and entertainment systems in a fundamental way, the true impact of which is difficult to predict.

This thesis presents a unified treatment of some of the issues related to interactive video service provision. Currently, there is much research being conducted on various aspects of these systems. The complex nature of large-scale interactive video systems has, however, often lead to the use of significant simplifying assumptions or isolated treatments of specific sub-problems. While these efforts are valuable, this thesis takes a more holistic approach. A top-down approach is used to perform a cost comparison of an entire network architecture, before considering various aspects of the system in more detail.

As a result of an extensive literature survey and preliminary investigations, several areas are isolated for further consideration. Specifically, the use of disk-array based storage for video servers is considered in detail. Performability analysis is employed to compare various disk-array architectures from a combined performance and reliability perspective. Further, a new packing scheme is introduced for allocating video objects to the various disk arrays within a server. This scheme is shown to give considerable efficiency improvements over existing packing heuristics.

Before transmission of video can commence, a video server must ensure that sufficient resources are available to support the call. Traditional call-admission control (CAC) procedures are shown to lead to high delay variability due to poor load balance. A new CAC scheme is proposed which utilises significant information about server state to improve load balance and reduce delay variability.

The thesis concludes with a methodology suitable for designing large-scale interactive video systems suitable for supporting video-on-demand style applications. The method applies the analytic tools presented earlier in the dissertation to provide the engineer with a robust method for top-down system design.

The results of this thesis lead to the conclusion that interactive video systems can be constructed cost-effectively utilising existing storage and networking technologies. The costs are, however, substantial and a high level of market penetration will be required to ensure that such systems are profitable in the medium-term.

Statement of Originality

This is to certify that the work described in this thesis is entirely my own, except where due reference is made in the text.

No work in this thesis has been submitted for a degree to any other university or institution.

Signed

Scott Anthony Barnett
18 March, 1997

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First I would like to thank my thesis supervisor, Professor Gary Anido. His knowledge and support has always been inspiring.

I also must thank all my colleagues at The Institute for Telecommunications Research. Lorraine de Vere, Chris Stacey and Tony Liu deserve special mention, and I wish them all well in the completion of their studies. This research group has certainly provided a fertile grounding from which to conduct my research.

On a more personal level, I must thank my mother, Barbara, and my brother, Karl, for their support through all my years of study. Without support like theirs I would never have even attempted to come so far.

My final and most heartfelt thanks go to my wonderful girlfriend, Louise. Without her love and encouragement, who knows.

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List of Abbreviations

2DVP	Two-Dimensional Vector Packing
ADSL	Asymmetric Digital Subscriber Line
ARIA	Australian Record Industry Association
ATM	Asynchronous Transfer Mode
B-ISDN	Broadband Integrated Services Digital Network
CAC	Call Admission Control
CATV	Community Antenna Television
CBR	Constant Bit Rate
CDL	Constant Data Length
CPE	Customer Premises Equipment
CPU	Central Processing Unit
CTL	Constant Time Length
DASD	Direct Access Storage Device
DAVIC	Digital Audio-Visual Council
EDF	Earliest Deadline First
FES	Front End Server
FF	First Fit (or Fast-Forward)
FFD	First Fit Decreasing
GOP	Group of Pictures
GSS	Grouped Sweeping Scheme
HFC	Hybrid Fibre Coax
IAL	Interleaved Annular Layout
ITU-T	International Telecommunication Union, Telecommunication Standardisation Sector
IVOD	Interactive VOD
MPEG	Motion Pictures Expert Group
MPEG-2-TS	MPEG-2 Transport Stream
MTTF	Mean Time To Fail
MTTR	Mean Time To Repair
NVOD	Near VOD

PCBR	Pseudo-CBR
PPV	Pay-Per-View
QoS	Quality Of Service
QVOD	Quasi-VOD
RAID	Redundant Arrays of Inexpensive (or Independent) Disks
RAM	Random Access Memory
REW	Rewind
SCSI	Small Computer Systems Interface
SSBF	Same Shape Biggest First
STB	Set Top Box
SVOD	Staggered VOD
TV	Television
TVOD	True VOD
VBR	Variable Bit Rate
VCR	Video Cassette Recorder
VL	Video Library
VOD	Video-On-Demand
VS	Video Server

1. Introduction

Education is not the filling of a pail, but the lighting of a fire.

- William Butler Yeats

1.1 Background

With the evolution of the Broadband Integrated Services Digital Network (B-ISDN), new telecommunications services are becoming viable. Although we cannot begin to imagine all the future services that will be offered, it is true that many of them will require transmission of multimedia with associated quality-of-service (QoS) guarantees. Specifically, video data (with synchronised audio) will form a major component of the traffic on future public communication networks. Further, it is likely that much of this video information will be stored and supplied to customers from remote video servers. This is distinct from video data that is generated and consumed in real time as would be the case in video-conference style applications. In this thesis we are concerned with the efficient storage and transmission of pre-recorded video in an interactive fashion to a large number of users.

We define interactive video services as those in which the user has some degree of individual control over the content of the video being received. The antithesis of this is the broadcast video services currently available to most consumers around the world. The most common example of an interactive video application is Video-on-Demand which can be readily thought of as a replacement for video rental

stores. Video-on-Demand, however, is just one example of an *application* that requires interactive video *services*.

Numerous technologies have recently matured to make the provision of interactive video services possible. As such the various difficulties of providing interactive video services have typically been studied in isolation, from the viewpoint of the technology concerned. It is one of the goals of this thesis to present a unified discourse on the major issues in interactive video provision while also providing important contributions in several areas. Specifically the dissertation aims to develop a methodology through which an interactive video network can be designed that is efficient, effective and reliable.

1.2 Overview

This dissertation examines the important issues regarding the provision of interactive video services in a public area broadband network. A preliminary examination of the topic reveals several important areas for consideration. Video compression, storage technologies, network architectures and protocols for ensuring QoS all require investigation. In an attempt to provide a logical structure, a top-down approach is used in this discourse. That is, high-level networking concerns are considered first and used to identify important areas of interest, before investigating the details of various components of the network architecture. A summary of each chapter is presented next.

Chapter 2 presents a critical review of current efforts in supporting interactive video, and identifies the shortcomings of some of the current work. This provides the motivation for the rest of the dissertation in which we take a unified approach to the problem of providing interactive video services to a large customer population. Chapter 2 also serves as a survey of the technologies that are required to provide interactive video services.

Chapter 3 examines the network design problem. Specifically we investigate the optimal dimensioning and placement of video servers and caches within a large-scale network to ensure maximum cost effectiveness. The output of Chapter 3 is a method of using distributed storage with appropriate caching policies to minimise both storage and bandwidth costs within the network.

With a network architecture essentially in place, Chapter 4 examines server design in order to determine the most efficient architecture for video provision. We examine hierarchical and disk based storage. Specifically, performability analysis is used to compare the various RAID (Redundant Arrays of Inexpensive Disks) options available in the use of magnetic disk technology. Performability analysis is a technique introduced to allow reliability and performance measures to be considered jointly, and a review of relevant literature is provided within Chapter 4. Further, this chapter presents and investigates the trade-off between reliability and blocking probability of large disk arrays.

Given a server storage architecture and a set of video objects to be served, Chapter 5 develops a placement policy for ensuring a minimal blocking probability for any user request. This problem is shown to be analogous to existing work in operations research. Relevant literature is reviewed and we compare our solutions with earlier proposals with favourable results.

Following the results of Chapters 4 and 5, Chapter 6 looks at the problem of call-admission to a coarse-grained disk array. Analytical and simulation methods reveal that the load is not inherently well-balanced in a coarse-grained disk array. This poor balance can be seen to manifest itself as highly variable delay to viewer admission and interactivity requests. A call-admission control (CAC) scheme is developed to improve this load balance and consequently reduce admission delay for new requests and interactivity delay for existing requests.

Chapter 7 utilises techniques developed in earlier chapters to form a logical design procedure for wide-area interactive video systems. This original design process is illustrated by way of an extensive case study.

Chapter 8 concludes the thesis with a summary of the major results obtained in the earlier chapters.

The following table provides an illustration of how the major topics discussed fit into a top-down approach, and also demonstrates the different timescales at which each aspect would typically occur.

Table 1.1 Top-down structure of thesis

Aspect of Operation	Timescale	Discussed in Chapter
Network Design	10's of years	3
Server Design	Years	4
Disk Array Design (Object Placement)	Days/Weeks	5
Admission Control	Seconds/Minutes	6

1.3 Contributions

Below is a list of the major contributions of this thesis. Contributions are sorted in approximate order of appearance, with section numbers indicating where the point is first discussed in the thesis and relevant publications also shown in parentheses. The fact that the contributions span a number of diverse topic areas is a legacy of the fact that interactive video systems are a direct result of the convergence of a number of maturing technologies.

1. Development of a cost model for magnetic disk drives based on a large survey of current prices from a variety of manufacturers (Section 3.3.1) ([Barn98]).

2. Accurate characterisation of Video-On-Demand workload based on available statistical data from the literature (Section 3.4.1) ([Barn95b] [Barn96c]).

3. Proposal of a heterogeneous storage system based entirely on disk array technology (Section 3.4.3) ([Barn95a] [Barn96c]).

4. Cost analysis of distributed and centralised storage in a wide-area interactive video network based on realistic network architecture (Section 3.5) ([Barn95a] [Barn96c]).

5. Development and validation of an accurate model of the dynamics of video popularity versus time (Section 3.6.1) ([Barn95b]).

6. Invention of appropriate caching algorithms to ensure cache currency in distributed interactive video systems (Section 3.6.2) ([Barn95b]).

7. Modelling of sustainable throughput for RAID 3 and RAID 5 disk arrays (Section 4.4.1) ([Barn96b][Barn98]).

8. Determination of minimum cost configuration for a disk array given throughput and capacity constraints (Section 4.4.1) ([Barn96b][Barn98]).

9. Development of time-dependent reward structures for RAID 3 and RAID 5 disk arrays which account for penalties due to disk failure in a read-only environment (Section 4.5.1) ([Barn96b] [Barn98]).

10. Development and solution of a three-state Markov chain for reliability of RAID disk arrays, accounting for single and multiple failures and repair times (Section 4.5.2) ([Barn98]).

11. Relaxation of Markovian assumptions on reliability and demonstration that the model is insensitive to such assumptions (Section 4.5.2.1).

12. Integration of performance and reliability aspects of disk array operation into a performability model suitable for evaluating revenue earning potential (Section 4.5.3) ([Barn98]).

13. Demonstration that RAID 5 disk arrays are generally preferable to RAID 3 by way of extensive cost versus revenue comparisons (Section 4.6) ([Barn96b] [Barn98]).

14. Mathematical description of the video object allocation problem and identification of the problem as a variant of the NP-hard two-dimensional vector packing (2DVP) problem (Section 5.3) ([Barn96e]).

15. Derivation of the applicability of Erlang's B formula to accurately model disk array blocking probability (Section 5.4).

16. Proposal and justification of a Gamma distributed model for movie length distributions (Section 5.5.1).

17. Development of useful upper and lower bounds on the solution to the 2DVP problem (Section 5.6).

18. Demonstration of the poor performance of existing heuristics for solution of the 2DVP problem with appropriate input distributions (Section 5.7.1) ([Barn96e] [Barn96d]).

19. Proposal of a new problem specific heuristic, Same-Shape-Biggest-First (SSBF), for near optimal solution of the 2DVP problem under appropriate assumptions for video object allocation (Section 5.7.2) ([Barn96e] [Barn96d]).

20. Confirmation of the significant improvements afforded by SSBF over previous heuristics (Section 5.8) ([Barn96d]).

21. Demonstration that coarse-grained disk arrays exhibit significant short-term load imbalance under conventional call-admission control schemes (Section 6.3).

22. Demonstration that such load imbalance leads to unnecessarily high call admission delay variation in large disk arrays (Section 6.3) ([Barn96a] [Barn97]).

23. Invention of a new "predictive" CAC scheme which utilises detailed array state information to improve array load balance (Section 6.4) ([Barn96a] [Barn97]).

24. Demonstration that the predictive CAC scheme reduces delay variance, and allows simple differentiation between admission and interactivity requests, permitting different QoS levels for each (Section 6.5) ([Barn97]).

25. Analysis of the sensitivity of the predictive CAC scheme to various system parameters, including disk array size, disk throughput and the level of user interactivity (Section 6.5).

26. Proposal and application of a top-down design methodology suitable for interactive video systems. (Section 7.2) ([Barn96d]).

1.4 Publications

Publications arising directly from work presented in this thesis are listed below:

1.4.1 Journal Publications

S. A. Barnett, G. J. Anido, "A Cost Comparison of Distributed and Centralised Approaches to Video On Demand", IEEE Journal on Selected Areas in Communications, Volume 14 Number 6, August 1996.

S. A. Barnett, G. J. Anido, "Performability of Disk-Array Based Video Servers", ACM/Springer-Verlag Multimedia Systems Journal, to appear Volume 6 Number 2, 1998.

1.4.2 Conference Publications

S. A. Barnett, C. H. E. Stacey, G. J. Anido, H. W. P. Beadle, H. Bradlow, "A Prototype Information Service Architecture in a Distributed

ATM Environment", Proceedings of ATNAC '94, 5-7 December 1994, Melbourne, Australia.

S. A. Barnett, G. J. Anido and H. W. P. Beadle, "Caching Policies in a Distributed Video-On-Demand System", Proceedings of ATNAC'95, 11-13 December 1995, Sydney, Australia.

S. A. Barnett, G. J. Anido and H. W. P. Beadle, "A Storage Cost Analysis of Video-On-Demand Architectures", Proceedings of ATNAC'95, 11-13 December 1995, Sydney, Australia.

S. A. Barnett, G. J. Anido, "An Efficient Non-Hierarchical Storage System for Video Servers", In Proceedings of the Multimedia Japan 96 (International Symposium on Multimedia Systems). March 18-20, 1996, Yokohama, Japan.

S. A. Barnett, G. J. Anido, "Design of Large-Scale Interactive Multimedia systems", Networks 96, Sydney, Australia, November 1996.

S. A. Barnett, G. J. Anido, "A Comparison of RAID Architectures for Video Services", Proceedings of ATNAC'96, 3-6 December 1996, Melbourne, Australia.

S. A. Barnett, G. J. Anido, "A Call Admission Control Scheme for Maintaining Load Balance in a Disk Array Based Video Server", Proceedings of ATNAC'96, 3-6 December 1996, Melbourne, Australia.

S. A. Barnett, G. J. Anido and H. W. P. Beadle, "Predictive Call Admission Control for a Disk Array Based Video Server", IS&T/SPIE Symposium on Electronic Imaging: Science and Technology - Multimedia Computing and Networking 1997, February 8-14 1997, San Jose, California, USA.

2. Review of Current Efforts in Interactive Video Delivery

If fifty million people say a foolish thing, it is still a foolish thing.

- Anatole France

2.1 Introduction

The literature is replete with recent publications dealing with interactive video delivery. The scope of these publications is broad, covering topics from hypermedia and video-indexing to statistical multiplexing gain and modelling of VBR video traffic. For the purposes of this thesis, the literature can be divided into two main categories: networking issues and server issues. It is therefore advantageous to divide the review presented in this chapter along the same lines. Before presenting a critical review of recent literature, however, we introduce interactive video services and describe some of the important technologies that will be required for its delivery (Section 2.2). In Section 2.3 we review networking aspects of interactive video delivery before examining the current state of technology in video servers in Section 2.4. Section 2.5 discusses trial systems and Section 2.6 gives an overview of standardisation in the area of interactive video. A summary of the chapter with regard to the remainder of the thesis is presented in Section 2.7.

2.2 Interactive Video Services and Technologies

Interactive video (or interactive TV) is a new service that gives consumers greater control over their program content than exists with conventional television systems. The viewer is able to select from an extensive range of video titles and affect the playback of these titles with VCR like control. Such a service is now possible due to recent advances in telecommunications and computing technology, combined with the convergence of the two.

To the consumer, interactive video will bring applications like Video-On-Demand, Home-Shopping and Network Games. These applications, along with a myriad of others will all be enabled by the same interactive video systems which are currently under development. The following sections define what interactive video services must provide to the applications; example applications are discussed and the enabling technologies for interactive video are introduced.

2.2.1 Definition of Interactive Video

First, an important distinction is made. We define interactive video as a *service*. Such a service is used by *applications*, which are controlled by users. The interactive video service will be used by all manner of applications in possibly quite different ways. Video-on-demand, for example, will playback long movies with little interaction, while home-shopping will require short clips with potentially high levels of interaction.

An interactive video system consists of three major components: video servers, a network and a viewers terminal (commonly called a Set-Top Box or STB) [Furh95]. Video material is stored on the server (in a compressed digital format), transmitted across the network, decoded by the STB and displayed on a standard TV. The video is interactive since the customer controls the selection and start time of the stream as well as performing interactive (VCR style) commands during playback.

The precise nature of the interactivity required by viewers is still largely unknown. Many market trials and surveys are currently underway, attempting to ascertain data on this and other issues (see Section 2.5.2). In the absence of such information, some assumptions regarding the capabilities required of an interactive video service are required. An absolute minimum set of functionality that must be enabled by any interactive video server would include:

- allow selection of a video clip of the customers choice from a large selection
- commence playback of the selected video object within a short time
- allow pausing of the current stream during playback and resumption of playback upon request

In order to provide a much more useful service, these basic abilities should be augmented with search facilities such as:

- jumping to a random location within the current video stream
- fast-play in both forward and reverse directions within the current video (ideally this would be available at variable rates)

It should be noted that a DAVIC compliant device [Digi95] is required to support all of these functions plus several others which are discussed in more detail in Section 2.6.

Various levels of interactivity have been classified by several authors. Generally they are classified in terms of the current most popular application: Video-On-Demand (VOD). In [Chan94c], Chang et al. use the terms IVOD (Interactive VOD), SVOD (Staggered VOD) and NVOD (Near VOD) to classify various granularities of interactivity. IVOD provides a dedicated stream per viewer and virtual VCR control. SVOD generates streams at intervals of a few minutes and viewers gain interactivity by jumping between streams. NVOD is a coarser version of SVOD with streams generated at intervals

between 5 and 30 minutes. The authors of [Budd95] use a similar three-level classification using the terms, dedicated viewing, shared viewing with constraints and shared viewing respectively. [Delo94] defines just two types of services (IVOD-i and IVOD-d), representing instantaneous and delayed interactive VOD. These map into Chang et al's IVOD and SVOD respectively.

In [Litt95] and [Gelm91] a five level classification scheme is introduced. We list them in order of increasing cost, starting with No-VOD which corresponds to broadcast TV. The next level is pay-per-view (PPV) where users are billed if they are watching but have no control over the stream. Quasi-VOD (Q-VOD) services group customers together based on the requested stream and start playback only when the group is sufficiently large. Near VOD (N-VOD) starts streams at regular intervals regardless of the number of customers. Finally True-VOD (T-VOD) starts a stream immediately for each customer request. This is clearly the most expensive and most interactive option.

It is clear that the required level of interactivity of a video service is poorly defined and as such it becomes difficult to compare different video server designs that support interactivity to various extents. The level to which interactivity is supported will be seen to have a considerable effect on interactive video server design and system cost.

2.2.2 Example Applications

Video-On-Demand, Home Shopping, Multiuser Games, Digital Libraries and Pay-per-view TV are all applications that will use interactive video services in some form. Undoubtedly the future will see other applications which have not yet been conceived. The application that has captured the imagination to date has been described as a replacement for video rental stores: Video-On-Demand.

By storing and serving feature length movies across a public broadband network it will be possible to obviate the need for video rental stores. Video-On-Demand (VOD) is the application aimed at providing this facility. VOD will be used as a case study throughout this dissertation. VOD is a useful case study for interactive video for several reasons. Firstly, the concept is well developed and its requirements are relatively well understood. Second, market research shows this to be clearly the most popular potential application among the general public [Ano95]. Finally, statistics are available from video rental stores which will aid in the design of VOD applications and hence interactive video services. Considering that a typical video rental store contains about 10,000 different videos each of which is on average 90 minutes long it becomes apparent that the provision of VOD is far from trivial. Recent trials of appropriate technologies have confirmed some of the difficulties in providing interactive video service to a large population.

A single feature length film requires at least 2 GB of storage when compressed according to the MPEG-2 (Motion Pictures Experts Group) standard (see Section 2.2.3). As such, an interactive video server supporting VOD will require terabytes of storage if it is to replace the local video store. Also a single video stream requires 3-4Mbps of server and network bandwidth for its entire duration and so the throughput required from a video server is also very high. Since some video titles are more popular than others, this throughput requirement will be unevenly spread across the objects stored on the server. By investigating the access patterns of videos from rental stores we can gain useful insight into the problem of video server and network design.

Statistics regarding the access patterns for videos at video rental stores are scarce. However, from the few published figures available, it is possible to gain an indication of the basic statistics of the hiring process. In [Bure94] a pie chart is shown (reproduced in Figure 2.1) which indicates the extreme skew in the distribution of movie popu-

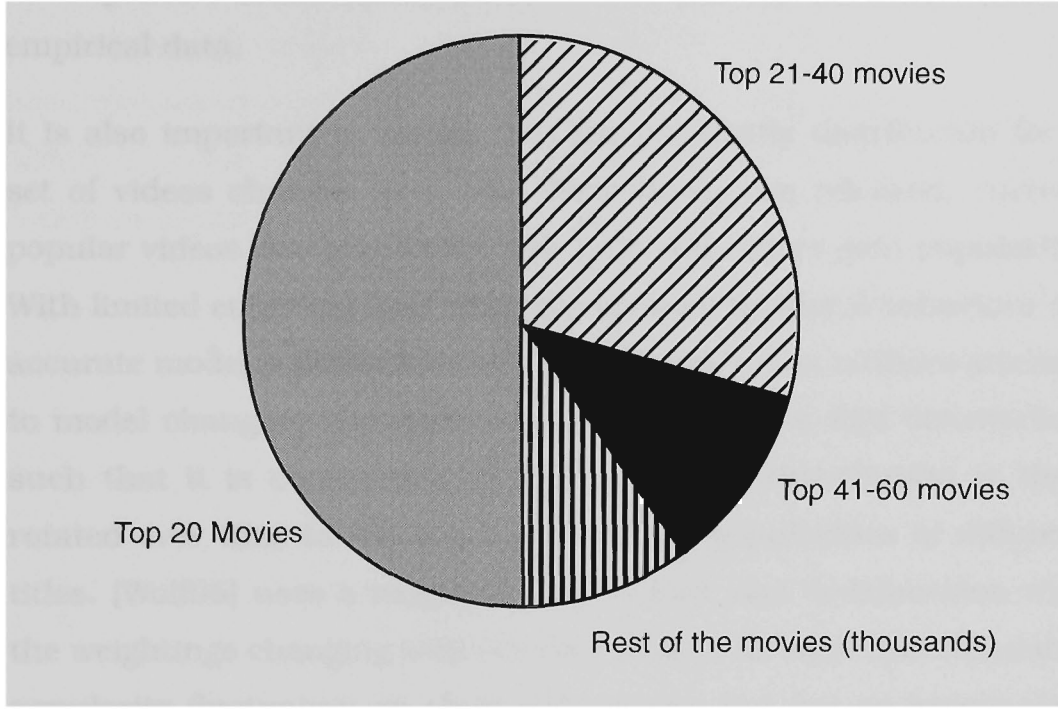


Figure 2.1 Typical frequency of hiring popular videos from video rental stores. Reproduced from [Bure94]

larity. Some authors have assumed even steeper skews with [Tetz96] suggesting that 10-20% of requests could be for a single title.

Given that average video rental stores have of the order of 10,000 different titles on offer, it is clear that the distribution of movie popularity at any time is initially a rapidly decaying function with a very long tail representing a large number of relatively unpopular titles. This popularity distribution is commonly modelled by Zipf's Law (see [Dan95a] [Nuss95] [Cher95b] [Chen95] [Wolf95]). This model is largely based on the work of Chervenak [Cher94], who showed, based on very limited data (one weeks video rental statistics), that the popularity of the top 40 movies is fairly well matched by the Zipf distribution. The extrapolation of this model to 1,000s of movies will be shown in Chapter 3 to be invalid.

Other earlier authors use geometric distributions [Doga94b], truncated geometrics [Bers94] or simpler piecewise linear models [Ghaf94] [Tetz94]. In Chapter 3 we compare various approaches and

develop a new model which is shown to be a better fit to the available empirical data.

It is also important to realise that the popularity distribution for a set of videos changes over time. New videos are released, current popular videos lose popularity over time and others gain popularity. With limited empirical data available on such temporal behaviour an accurate model is difficult to define. In [Dan94c] the authors attempt to model changing popularities by transforming a Zipf distribution such that it is continuous and periodic. The distribution is then rotated over time to effectively change the popularities of different titles. [Wolf95] uses a weighted sum of four Zipf distributions with the weightings changing with the time of day. As such this simulates popularity fluctuation on short time scales, but not on longer time scales. Neither of the above approaches has been shown to match well with empirical data. In Chapter 3, we define an algorithmic model for popularity change, which is shown to give good performance when compared to empirical data.

2.2.3 Key Technologies

Many authors attribute the current interest in interactive video to the concurrent maturity of several different technologies. Specifically, video compression, high-bandwidth access network architectures, ATM switching, and magnetic storage technology (discussed in Section 2.4.1 and 2.4.2) have all developed separately but can now be integrated to provide interactive video services to the home [Mino95].

2.2.3.1 Video Compression

Raw digitised video requires bandwidth on the order of 100 Mbps. [Bers94] quotes figures ranging from 45Mbps for NTSC television to 800Mbps for HDTV. Fortunately, video is inherently highly redundant. By accounting for both spatial and temporal redundancies, video compression algorithms are able to achieve compression ratios

up to 40:1 (but not the 100:1 often cited). By far the most commonly used video compression algorithm is MPEG [LeGa91], which has been standardised for use in interactive video applications [Digi95]. MPEG-2 is designed to give VCR quality video at a bit rate of about 3-6Mbps [Dixi95].

MPEG video uses three different frame types to exploit much of the temporal redundancy in video: I, P and B frames. I frames are intra-coded, this means that they make no reference to other frames. P frames are predictive and make use of information in the preceding I (or P) frame to reconstruct the current image. B frames are bidirectional and use information from an I or P frame both before and after the current frame to reconstruct the image. Figure 2.2 shows a sequence of frames and illustrates their temporal dependencies.

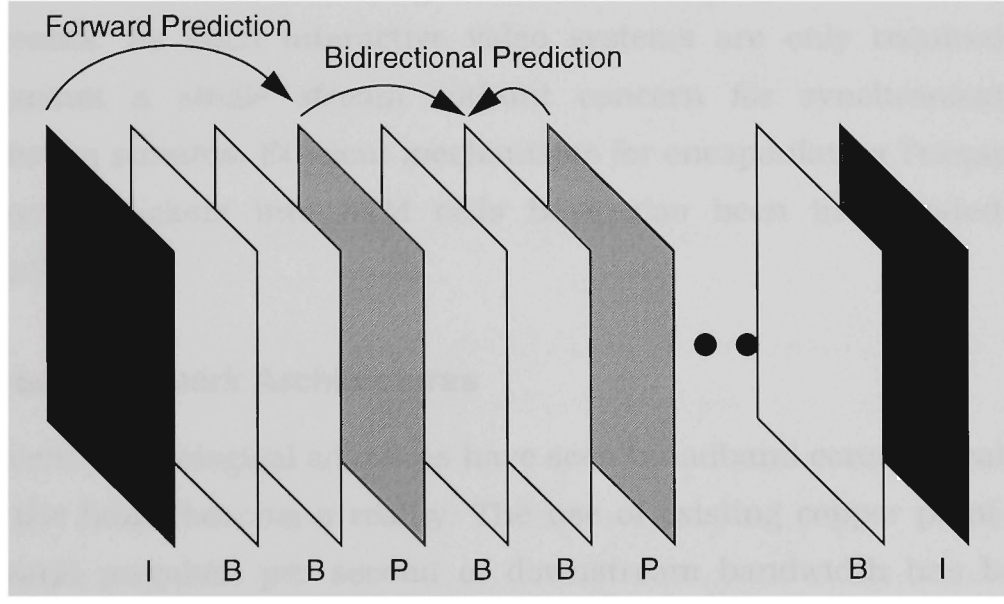


Figure 2.2 MPEG frame temporal relationships

I frames are repeated periodically so that in the case of an error the picture can be fully restored when the I frame arrives. The set of frames lasting from one I frame to the frame before the next I frame is called a Group of Pictures (GOP). A single GOP will generally equate to between $^1/_2$ and 2 seconds of video. Due to the varying type or amount of compression used on each frame type (and at the slice and macroblock levels), an MPEG stream is variable bit rate

(VBR). Of course different content in each frame means that even frames of the same type can differ considerably in size. As a guide, however, the ratio of I:P:B frame sizes is approximately 4:2:1 [Chen94a]. To simplify transmission, techniques are available to make the stream Constant Bit Rate (CBR) at the GOP level (ie. Pseudo-CBR or PCBR [Chan94b]). These techniques rely on feedback mechanisms which result in a variable quality output to ensure each GOP is the same number of bits [Chan94a]. It should be noted that even with open-loop VBR encoded video streams, the variability at the GOP level is much lower than the variability in bit rates of individual frames. A useful discussion of MPEG statistics at various levels is provided in [Panc94].

Although not discussed here in any detail, MPEG-2 provides "Transport Streams" which contain synchronised video, audio and data streams. As such interactive video systems are only required to transmit a single stream without concern for synchronisation between streams. Efficient mechanisms for encapsulating Transport Stream packets into ATM cells have also been investigated in [Lin96b].

2.2.3.2 Access Network Architectures

Recent technological advances have seen broadband communication to the home become a reality. The use of existing copper plant for several megabits per second of downstream bandwidth has been made possible by ADSL (Asymmetric Digital Subscriber Line) technology [Chen94c]. Overcoming the upstream bandwidth limitation of this ADSL are architectures such as Hybrid-Fibre Coax (HFC) which is currently widely deployed for analog CATV networks. Numerous other network technologies are also becoming cost effective. Even radio technology has recently been proposed for residential area broadband services [Celi96]. All of these architectures share the concept of separate access and backbone networks [Chan94c]. We depict a generic network architecture in Figure 2.3 which highlights

the requirement for a headend (or Front End Server (FES)) at the junction of the core and access networks.

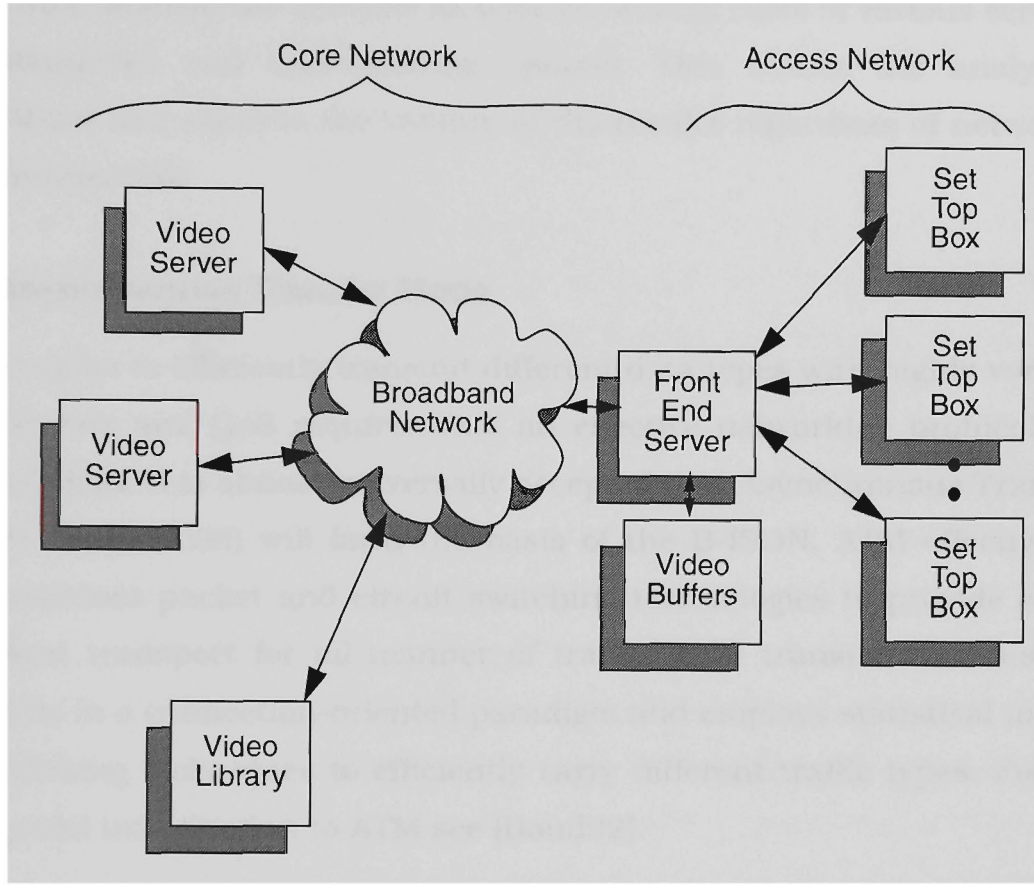


Figure 2.3 Generic interactive video network architecture

The generic network architecture of Figure 2.3 requires the use of a Front-End Server which transfers the video signal from the core network to the access network. The precise function of this device is dependent on the network technologies being employed but as a minimum it will perform demultiplexing and physical layer conversions. Other functions may include billing, authentication, and admission control. As such considerable functionality will certainly be required at the FES [Chan94c]. This makes the FES an essential network element independent of the networking technology or topology used.

Although assumptions can be made regarding the core and access network topologies (as is done in [Nuss95] and [Papa95] (see Section 2.3.2) in this thesis no such assumptions are made. The net-

work analysis presented in Chapter 3 makes no assumptions regarding the network, other than that concerning the existence of FES's. Instead the analysis focuses on storage costs of various server placement and dimensioning options. This makes the analysis robust and ensures the validity of the results regardless of network architecture.

2.2.3.3 Asynchronous Transfer Mode

In order to efficiently transmit different data types with highly variable rate and QoS requirements an effective networking protocol is required. It is almost universally accepted that Asynchronous Transfer Mode (ATM) will form the basis of the B-ISDN. ATM effectively combines packet and circuit switching technologies to provide efficient transport for all manner of traffic. ATM transmits fixed-size cells in a connection-oriented paradigm and employs statistical multiplexing techniques to efficiently carry different traffic types. For a useful introduction to ATM see [Boud92].

ATM provides several different service classes for different types of traffic. The realtime VBR and CBR service types are most useful for interactive video services since they provide a guarantee on delay and jitter experienced by all cells in the stream. More details on service classes for interactive video can be found in [Rich95]. We don't provide any further consideration of ATM technology here as it is not a focal point of this thesis.

It is clear that numerous technologies have now matured and converged to a point where interactive video services are viable. With a basic understanding of these technologies in place we proceed in the following sections to review the current efforts made toward making such services an economical reality. We begin with the network design issues.

2.3 Network Design Issues

Transmission of digital interactive video poses interesting problems for network designers. Essentially, the problem is to transmit an inherently variable bit rate stream with strict real-time constraints while maintaining high network utilisation and predictable quality of service to other traffic. The overall network topology is constrained by technological factors as well as financial and geographical ones. The current literature addresses these issues with varying degrees of rigour.

Work on the design of interactive video networks can be divided into two main categories. First, we consider the issue of transmitting variable-bit-rate video traffic over ATM links. Much work has been done focusing on the multiplexing of MPEG video sources to obtain efficient utilisation of broadband network links. The second issue concerns server dimensioning and placement within the broadband network. This work must consider the salient properties of interactive video when designing the network. We consider each issue in turn.

2.3.1 VBR Video Transmission over ATM

The MPEG-2 video compression algorithm is capable of providing VHS quality video with data rates of about 3-6Mbps [Dixi95]. It is highly likely that a first generation of video servers will use this algorithm for storage and transmission of video streams.[1] As already mentioned, ATM is the networking technology to be used for the B-ISDN. As such, we require an efficient scheme for transmitting MPEG-2 over ATM. Recent work [Lin96b] has defined an efficient method of packing MPEG-2-TS packets into ATM cells for transmission. The problem then becomes one of transporting these cells across a network in compliance with a set of QoS requirements. Cur-

1. Note that in the remainder of this thesis we use the term "video" to refer to a combination of video and audio as is contained in MPEG-2 Transport Streams (MPEG-2-TS).

rently, many trial systems simply use peak-rate allocation which would seem to be inefficient for the VBR nature of MPEG-2 data. In academia there have been considerable efforts in VBR video modelling in order to obtain statistical gains during transmission. [Aldr96], [Kana94], [Habi96] and [Krun95] are representative of recent efforts involved with the transmission of VBR video data over ATM style networks. The issue of VBR video transmission is not a focus of this thesis and so is not discussed here in any more detail.

2.3.2 Network Architectures for Interactive Video

Due to the high bandwidth requirements of digital video, the network architecture (and server placement) must be given careful consideration. As already seen in Figure 2.3 the network can be divided into two basic sections: the core network and the access network. Customers are connected to an access network. Individual access networks are connected together by a core network with higher capacity. In general, a customer will request information which is stored in a server located somewhere "within" the core network.

Given such a network architecture we must consider how best to locate and dimension our servers in order to minimise cost. Some authors have looked at this problem, but their work is flawed by some unrealistic assumptions.

In [Loug94] a methodology is proposed for server placement and replication which is analogous to the use of RAID in disk arrays. Lougher et al. suggest the use of mirroring (where servers are duplicated around the network) or striping where each server only stores a portion of each movie and they co-operate to serve a given request. Such a scheme requires servers to be highly reliable since a single server outage will result in all servers being unusable. Also many connections will be required between users and servers, for the retrieval of each video stream. This scheme is unnecessarily complex and cannot be seen to give any significant advantages. Lougher et al.

present no results to suggest that such a scheme is workable and as such we ignore this proposal pending future work.

[Papa95] introduces the idea of a Personal Service Agent (PSA). A PSA is a broker responsible for co-ordinating the retrieval and transmission of a video stream from a storage provider through a network provider to the user. They then formulate an extremely unrealistic distributed architecture and develop heuristics to serve user requests at minimum cost. The authors assume a network structure as shown in Figure 2.4.

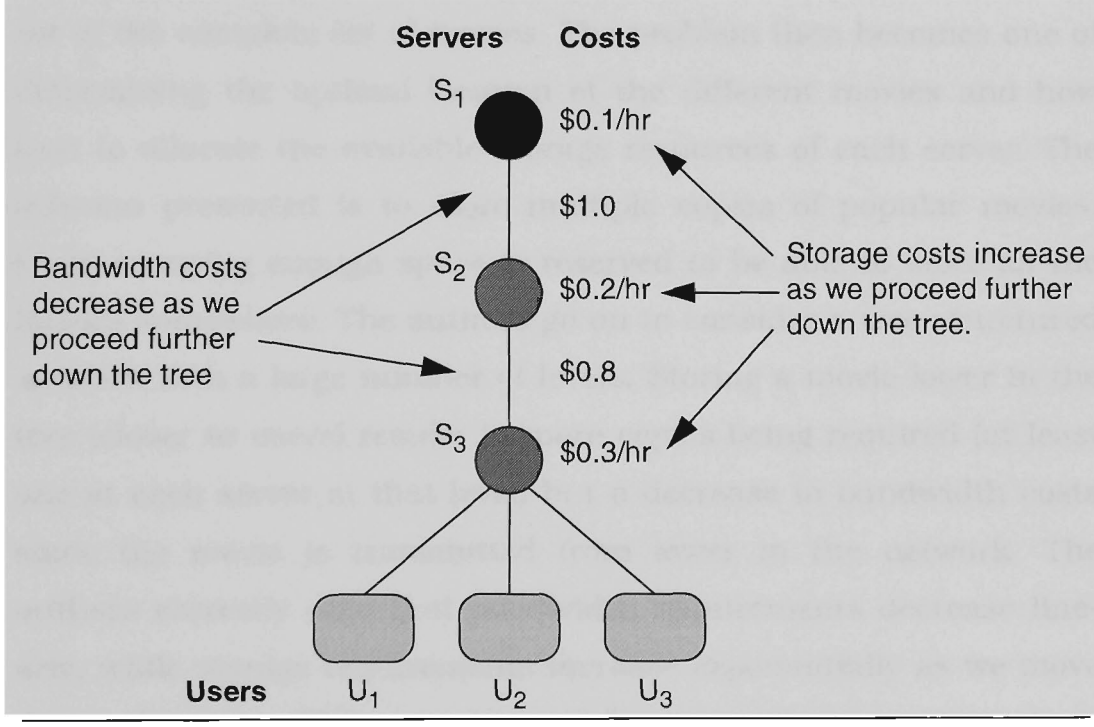


Figure 2.4 Network architecture and costs assumed by [Papa95]

Note that the cost of a unit of storage increases as we descend the graph toward the end user, while transmission cost decreases. These assumptions are totally unjustified. Although transmission costs may decrease closer to the access network, there is no reason to believe that storage costs increase. Also the authors make no attempt to model video popularity and instead assume that the PSA has advanced knowledge of all future movie requests. Based on these assumptions the authors heuristically solve the simplified problem of determining the optimum caching schedule at the servers

located at different levels of the graph. The solution is straightforward, but unlikely to be useful in a realistic network scenario where the author's assumptions will not hold. A more realistic model is to assume that a fixed amount of storage will be available at each level of the hierarchy and that it is best to use this storage as efficiently as possible. It is this model that is used in Chapter 5 where efficient solutions are developed.

In [Bisd95] and [Bisd96] the authors consider the case of a group of video servers distributed around a network with a total storage sufficient to store all movies, but where each server can only store a subset of the complete set of movies. The problem then becomes one of determining the optimal location of the different movies and how best to allocate the available storage resources of each server. The solution presented is to store multiple copies of popular movies, while ensuring enough space is reserved to be able to store all the movies somewhere. The authors go on to consider a tree structured network with a large number of levels. Storing a movie lower in the tree (closer to users) results in more copies being required (at least one at each server at that level) but a decrease in bandwidth costs since the movie is transmitted from lower in the network. The authors correctly note that bandwidth requirements decrease linearly, while storage requirements increase exponentially as we move down the tree. They assume, without justification, that these requirements are directly proportional to the associated costs in both cases. By their own admission Bisdikian and Patel present only limited, preliminary numerical results which indicate that considerable storage should be located fairly low down in the network hierarchy. This paper and the following one by Yoshida et al. both suffer from a simplistic model of server cost which fails to account for the combination of storage and bandwidth requirements of the video server.

[Yosh96] is a recent study of object allocation to servers distributed across a network. In a similar manner to [Papa95] and [Bisd95], the

authors formulate a simplified problem and use mathematical programming and heuristic approaches to find solutions. In the case of [Yosh96] for example, total system cost is represented by a single coefficient (C) multiplied by the number of video objects stored within servers around the network. For the case studies presented, C is arbitrarily assigned a value of 10. No effort is made to account for individual object sizes or popularities, or the physical nature of the storage provision within each server. Despite the unrealistic cost models used, the results of [Yosh96] tend to indicate that small caches should be distributed around the network, located as close to customer populations as possible.

[Nuss95] provides a detailed discussion of networking requirements for interactive video. Nussbaumer et al. derive analytic models for cost of servers and links in a tree structured network. Assuming a Zipf distribution of movie popularity they study the placement of caching within different levels of the hierarchy. Results show that over a wide range of parameters, caching at a level of about 80% of the depth of the tree is optimal. This is said to correspond to just above the head-end. The analysis presented in [Nuss95], however, assumes that video server cost is directly proportional to the total popularity of the movies being stored. They make this assumption despite the recognition that the cost of a server is related to both the number of movies stored and their relative popularities. Although the cost function used by Nussbaumer et al. may apply if the system is bandwidth limited, the authors make no effort to show that this is the case. Further, an appropriate model of disk cost (where cost is a concave function of disk capacity) would have further altered the cost model and hence the results seen in [Nuss95]. This work is considered in more detail in Chapter 3 where a more appropriate cost model is proposed.

It is clear that previous literature has approached the problem of network dimensioning and server placement from various directions. All approaches, however, feature some form of cost model for storage

and/or bandwidth. In Chapter 3, we use a more detailed model of server cost (one based on a physically realisable model of server architecture) to perform a similar analysis to that of Nussbaumer et al. The analysis is, however also unique in that no assumptions are made regarding physical network structure (other than the existence of core and access networks). Further, demand and change in demand are modelled more accurately than is done in [Nuss95], as well as incorporating bandwidth and storage costs along with a validated model of disk cost.

Having considered network design issues, we proceed to now consider a subset of the myriad of server design issues.

2.4 Server Design Issues

Video servers are the source of video data which is then transmitted across a wide-area network. Applications such as those identified in Section 2.2.2 rely on these servers to provide real-time video content to customers. In a large network the quantity of video traffic that will be supplied by these servers will be immense. In effect a video server is a massive I/O machine capable of sustaining many megabytes per second throughput with minimal delay or jitter. The problems associated with constructing such a server and making it cost effective are many. Much literature is currently appearing dealing with each of these problems, normally in an isolated manner.

The overwhelming theme in this literature is that the area of video servers is yet to mature with fundamental results still being produced. Papers are currently appearing with such frequency that it is difficult for each to fully account for work contained in the others. As a result we see similar ideas developed concurrently with slightly different emphases. This section aims to unify this constantly expanding body of knowledge by identifying the major options for different aspects of video server design. It becomes clear that there are several

fundamental choices to be made in video server design and with thorough reference to the literature we compare these choices and identify key trade-offs with each. It should be noted that the trend of considering interactive video in terms of the video-on-demand application is followed, although most of the results presented can be generalised to other interactive systems.

A design brief for an interactive video server is quite concise. Essentially, it must store and serve a large number of videos to a large customer population with real-time constraints. More verbosely, a video server must:

- store a large number of objects (videos) each of which, after compression still occupies in the order of two gigabytes of storage.
- retrieve these objects independently to a large number of customers with strict real-time constraints.
- support interactivity in the form of random searches, pauses and other requests.
- respond to user requests with a minimum delay
- be reliable and dimensioned to be highly available to the viewing population (ie. guarantee a low blocking probability)
- cost little enough to enable a rapid and widespread penetration into a large proportion of the market

One aspect that has a major effect on server design is interactivity. The type and quality of interactivity dictates many aspects of server design. As will be shown, much of the literature ignores interactivity issues altogether. Perhaps this is because the interactivity requirements of users are currently not well understood and as such it is difficult to design servers in the most efficient manner. Throughout the remainder of this chapter we will illustrate where interactivity requirements effect server design.

As already discussed in Section 2.2.2 a set of video objects will exhibit an extreme locality of reference, whereby a small number of items constitute a large number of requests. In order to meet the criteria set out above with such a varying popularity function, clearly a video server must be able to allocate bandwidth resources dependent on the demand for a particular object and independent of other demands. The server must also be able to vary this allocation over time in response to changes in movie popularity.

When we consider that the most popular movie may be requested concurrently by hundreds of users we clearly require a storage subsystem with extremely high bandwidth availability[2]. At the other end of the scale we have the least popular movies, which although requiring basically the same storage capacity, are hardly ever requested and as such require very little bandwidth. This realisation immediately prompts the idea of a storage hierarchy in order to meet the highly variable demands for bandwidth for different objects.

2.4.1 Storage Hierarchies for Interactive Video

The discussion above has shown that Video-on-Demand applications will generate widely varying access rates for different objects. It is reasonable to believe that this will also be the case for other interactive video applications. As such an interactive video server must be able to efficiently handle objects with similar capacity requirements but very different bandwidth requirements.

It is intuitively pleasing to use a storage hierarchy to satisfy this variation in demand. A storage hierarchy would consist of various different types of storage chosen to cater for the bandwidth requirements of the objects being stored in it. In other words popular movies can be stored in fast storage (RAM), less popular movies stored on magnetic disk or optical disk, while very unpopular movies

2. Note that in True-VOD every customer request translates directly to an extra stream of bandwidth. With other levels of service this can be reduced (refer to Section 2.4.6 for more details).

could be archived on tape. [Bure95] presents a useful discussion of different storage media and their position in a storage hierarchy determined according to access speed and cost per unit of storage. Figure 2.5 illustrates the concept of storing movies at different levels of the hierarchy according to popularity.

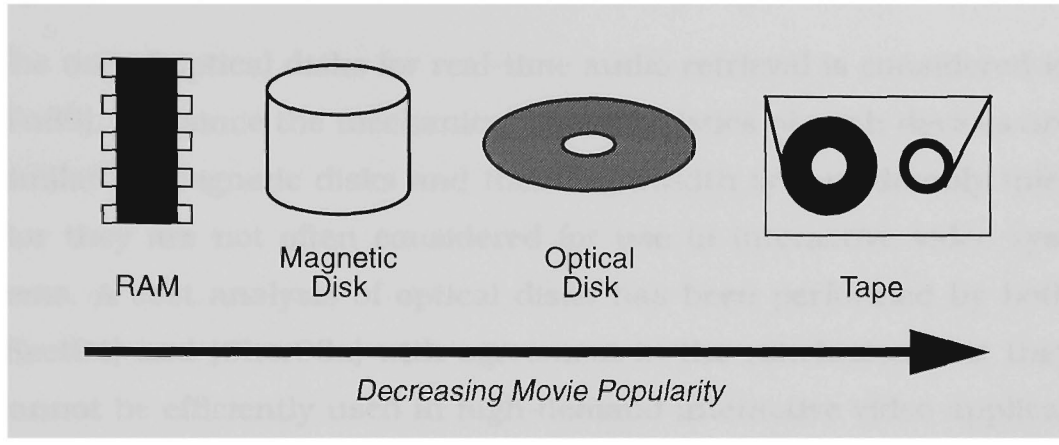


Figure 2.5 Illustration of storage hierarchy for interactive video servers

The literature abounds with proposals and analyses of such hierarchical storage systems in a number of different forms. We consider each device in turn.

2.4.1.1 Magnetic Tape

Tape systems exhibit the lowest cost per megabyte of storage and as such make an attractive option for archival storage of large bodies of data [Cher95b] [Keet94]. High-end tape systems also exhibit reasonable sustained bandwidth but interactivity is poor due to the sequential nature of the medium and delay can be high if robots are used to load the requested tape. Pipelining mechanisms are proposed in [Ghan95a] and [Lau95b] with the aim of decreasing interactivity delays. Although such schemes can clearly provide lower delays, it is at the cost of more wasted time spent in tape swapping and consequently a lower utilisation of the system for reading. [Doga94b] proposes the use of "staging" disks which act a a smoothing buffer between the tape drives and the client playout buffers. They also propose the use of "leading" disks which allow immediate

start by storing the beginning of each title on disk and retrieving the remainder from tape once playback has commenced. These schemes ameliorate some of the problems of tape based multimedia but increase total system costs.

2.4.1.2 Optical Disks

The use of optical disks for real-time audio retrieval is considered in [Yu89], but since the mechanical characteristics of such devices are similar to magnetic disks and their bandwidth is considerably inferior they are not often considered for use in interactive video systems. A cost analysis of optical disks has been performed by both [Keet94] and [Cher95a] with agreement in the conclusion that they cannot be efficiently used in high-demand interactive video applications.

2.4.1.3 Magnetic Disk

Magnetic disk is universally agreed upon as a most suitable storage medium for interactive video applications. Magnetic disks are not inherently well-suited to such strictly real-time applications, but solutions are available that minimise the problems. We consider the issues involved and proposed schemes for the use of magnetic disks (and disk arrays) in Section 2.4.2. Since disks are available with varying sizes and bandwidths it is possible to create a storage hierarchy using disk technology alone. This idea is first proposed by us in [Barn95a] [Barn96c] and is presented in detail in Chapter 3.

2.4.1.4 Random Access Memory

The use of RAM for extremely popular requests has been suggested by numerous authors. [Doga94b] for example suggests that if a movies popularity is more than 144 times its length it should be stored in RAM. Of course this figure is heavily dependent on the assumed cost and characteristics of each medium. Similarly, [Stol95] determines an appropriate cutoff between disk and RAM for popular

titles. [Tetz94] also suggests that in time random access memory will be a necessary part of the interactive video storage hierarchy. Work by others (including Dan et al. in [Dan94c]) draws the opposite conclusion that RAM is never an economical solution for storing entire movies. In Chapter 5 we will present results based on disk array based storage that form a fundamental argument against the need for RAM for storing entire movies.

2.4.1.5 Evaluation of Hierarchical Systems

A consensus on the design of the storage system in a video server is far from being reached. Magnetic disks will most certainly feature in the hierarchy. Optical disks will probably not be used, at least until the current drives improve considerably. Tape and RAM each have proponents and opponents. Several authors state (without proof) that disk is too expensive to provide the entire storage requirements of an interactive video server [Cher94]. As such tape is commonly assumed to exist in the storage system [Lau95b] [Lau96] [Ghan95a]. In general the studies analysing the cost of hierarchical systems have, to date, been unrealistic. This section reviews the existing literature in this area.

When providing interactive services it is the cost per stream that must be minimised [Cher95a]. This is because customers will be charged for the bandwidth they consume, not based on the number of objects held on any particular server. A low cost per unit of storage does not necessarily translate to a low cost per stream. Once this realisation is made it is no longer obvious that tape based systems provide economical advantages. Indeed Tetzlaff et al. presents a simple framework for the comparison of various storage systems which illustrates the importance of considering the cost per stream as a figure of merit [Tetz94]. Using some simplifying assumptions, Tetzlaff et al. develop a simple analytic expression to determine the number of storage devices required in a given multimedia server. Using this model they evaluate several storage approaches based on the cost

per stream. Tetzlaff concludes that RAM will have a place within the storage hierarchy for interactive video, but due to the high cost per stream, current tape systems are not a viable alternative.

A tool for cost estimation of hierarchical storage servers has been developed by Doganata and Tantawi [Doga95] based on work presented in [Doga94b] and [Doga94a]. This tool uses simple analytic models to determine the optimal division of movies to levels of the storage hierarchy. The assumptions and models used are quite unrefined and as such potentially inaccurate. Particularly, tape drives are assumed to be non-blocking; implying that a tape drive is always available for a new request. In an overdimensioned system this may be true, but given the high cost of tape drives, queueing will take place and increase the predicted delays.

In her PhD thesis [Cher94], Chervenak evaluates video-on-demand as a potential application of tertiary storage. Also, in [Cher95a] the authors compare disk arrays (or farms) with an hierarchical system using a discrete-event simulation. Although only basic designs of each system are simulated, the models appear quite valid and incorporate realistic cost estimates of the various devices. The conclusion reached is that neither tape drives nor optical disks can be employed in real-time multimedia servers in a cost effective manner.

Keeton et al. [Keet94] presents a similar simulation study and draws the same conclusion. That is, that tape based systems do not provide sufficient throughput to be economically justifiable in a large-scale interactive video server.

Of course all of the above results are highly dependent on the assumptions made concerning the cost and performance of the various devices. The rapidly changing and highly variable costs of such devices make these results difficult to generalise, and as will be seen in Chapter 3 this continues to be the case, with any cost model being almost immediately out of date.

As already mentioned, a consensus on the utility of hierarchical storage is yet to be reached. Given that magnetic disk technology is required in any interactive video server, we focus (as does the literature) on the adaptation of this technology to such a real-time service. Indeed it will be proposed (in Chapter 4) that disk technology can be used for the entire storage system in an economical fashion. None of the current research has conclusively shown that hierarchical systems can achieve such a goal.

In the next section we consider disks and disk arrays and the literature concerning their use for real-time storage and retrieval. A large focus of the remainder of this thesis is aimed at showing that disks can be used to meet the entirety of storage requirements in a video server.

2.4.2 Disk Arrays for Video Service

All previous work discussing video servers recommends the use of disk arrays in some form, in the storage hierarchy. Although disks have limitations in real-time applications, they currently seem to provide the best trade-off between cost, capacity and throughput. This section introduces the basic consideration of using disk arrays to serve real-time video. We start with a general discussion of disk technology. The following sections discuss some of the active research in this area.

Magnetic disks[3] have long been the dominant form of mass storage in computer systems. For most systems they provide a suitable balance of high throughput and low cost per bit as well as small physical size. Ruemmler and Wilkes provide an excellent discussion of magnetic disk technology and of appropriate models to be used to determine the performance of disk drives in various environments [Ruem93] [Ruem94].

3. The terms magnetic disk, hard disk, and disk drive are all used synonymously in this thesis.

A typical disk drive will consist of several *platters* all attached to a common *spindle* which rotates at a fixed speed. Each platter surface has an associated *disk head* that is responsible for both reading and writing of data. All disk heads are moved synchronously with only one head actively reading at any time. Each platter is divided into a large number of concentric circles called *tracks*. (Each track is further divided into *sectors*). The corresponding tracks on all surfaces form a *cylinder*. The drive reads from different tracks within a cylinder, without moving the heads, by performing a *head switch*. An illustration of a hard disk is shown in Figure 2.6[4].

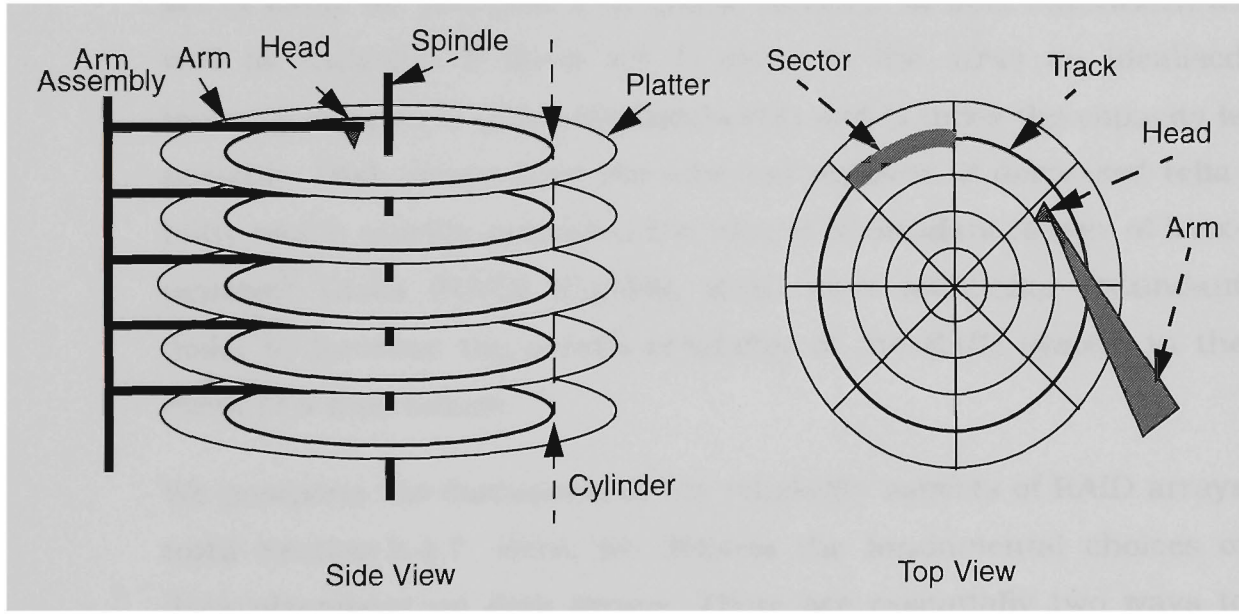


Figure 2.6 The mechanical components of a disk drive (from [Ruem93])

When a request is serviced by a disk, the following sequence of events takes place:

- the heads seek to the appropriate track of the disk (a seek consists of four phases: speed-up, coast, slow-down and settle)
- once the heads have settled the disk rotates until the appropriate sector is under the head and then reading takes place

4. Although not illustrated in the figure, most modern disks have more sectors per track at the outside of the disk, than at the inside. Since angular velocity is constant, this results in a higher data rate from the outside tracks than the inside.

- the head continues transferring data until the request is complete or until it reaches the end of the track.

- At the end of a track it will perform a head switch to read the next track in the cylinder, once a cylinder is exhausted it will seek to the next track to continue serving the request.

In order to increase capacity and throughput, individual disks can be combined together in arrays. Disk arrays are essentially just groups of individual disks. Data is placed across all the disks in the array using various forms of "striping". By striping the data across a set of disks we can gain a dramatic increase in disk bandwidth as well as capacity. If there are D disks in the array an idealised increase of up to D times the bandwidth and D times the capacity is possible. Disk arrays have the inherent problem of decreased reliability which quickly prompted the idea of Redundant Arrays of Inexpensive[5] Disks (RAID) [Patt88]. RAID uses additional redundant disks to increase the overall reliability of the RAID system in the event of a disk failure.

We postpone the discussion of the reliability aspects of RAID arrays until Section 2.4.7. Here, we discuss the fundamental choices of data placement on disk arrays. There are essentially two ways to stripe data across a set of disks: fine-grained and coarse-grained striping [Gang94]. Both forms of striping involve placing sections of an object on each of the disks in the array. The difference is in the size of the sections, and the service policy. Refer to Figure 2.7.

Fine-grained striping is otherwise known as bit or byte level striping. Data is striped in very small sections across disks and requests are serviced in parallel by all the disks in the array. This implies that every disk in the array contains a fraction of every accessible block. When a request is received by the disk array, all disks act in a syn-

5. Note that "Independent" (or even "Individual" [Frie96]) now commonly replaces "Inexpensive" in the RAID acronym.

chronised fashion to retrieve the request, with each disk retrieving 1/D of the request.

Coarse-grained striping allocates larger blocks of each object to each disk in a round robin fashion. Hence, a large request will be served by accessing each disk in succession, while smaller requests are satisfied by a request to a single disk of the array.

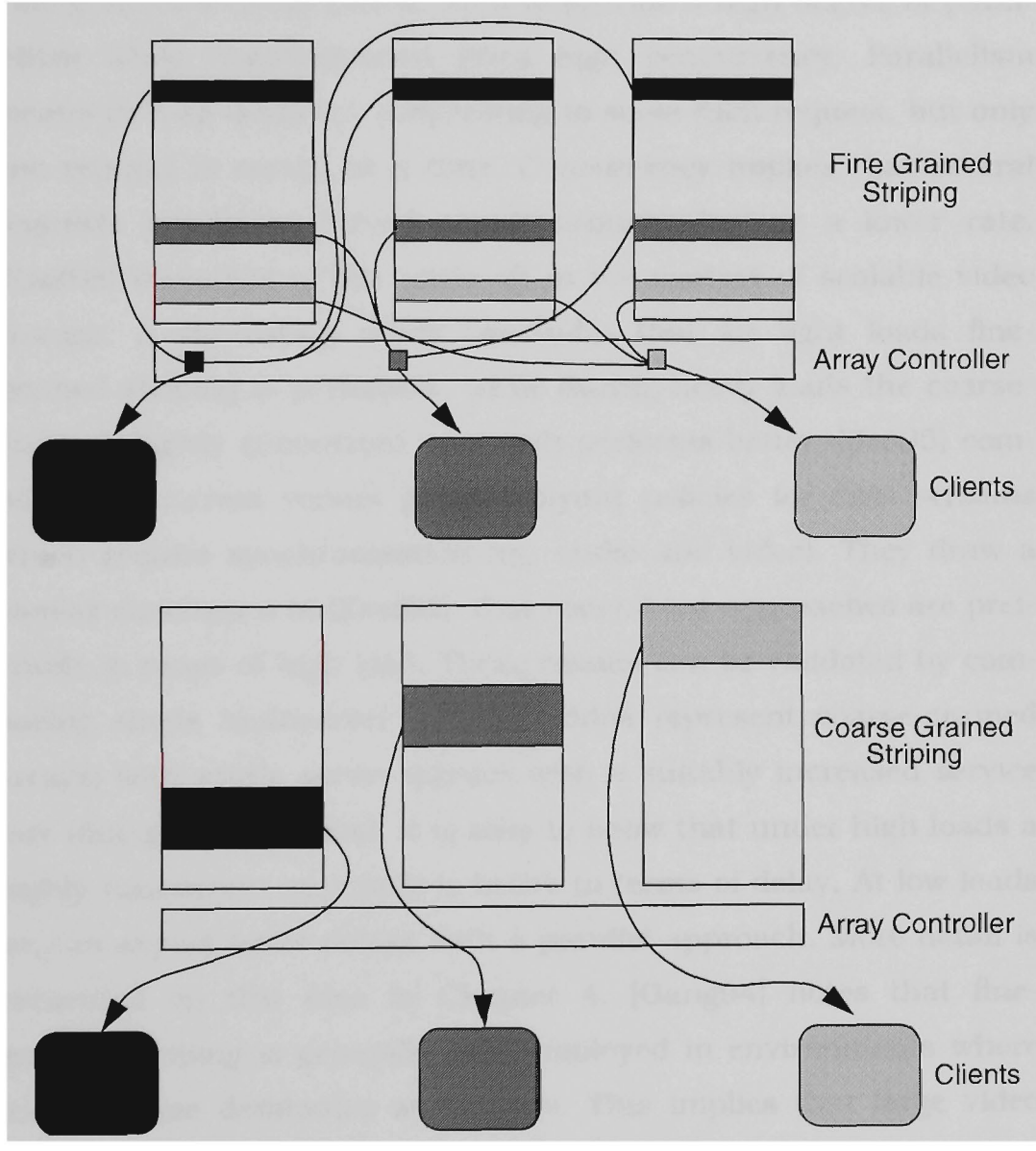


Figure 2.7 A comparison of fine and coarse grained striping in disk arrays with 3 disks serving a total of 3 requests in each case

Fine-grained striping gives a higher throughput for each individual request (ideally by a factor of D, although this is unobtainable), while coarse-grained striping shares the load over a large number of disks

and hence potentially reduces the waiting time of a request in a typical system. Note, however, that even for a single disk, the time to retrieve a video block is lower than the playout time. As such an increased data transfer rate per request (as provided by fine-grained striping) is not required in interactive video systems. There are, however, other trade-offs between the two techniques.

Fine-grained striping can be seen to provide a high degree of parallelism while coarse-grained gives high concurrency. Parallelism means that all disks are cooperating to serve each request, but only one request is served at a time. Concurrency implies that several requests are being served simultaneously, but at a lower rate. [Keet95] investigates this trade-off in the context of scalable video storage. A simulation study concludes that for light loads fine-grained striping is preferable, while during heavy loads the coarse-grained, highly concurrent approach performs better. [Seo95] compares concurrent versus parallel layout policies for data streams which require synchronisation (eg. audio and video). They draw a similar conclusion to [Keet95]: that concurrent approaches are preferable in cases of high load. These results can be validated by comparing single multiserver queues (which represent coarse-grained arrays) with single server queues with a suitably increased service rate (fine-grained arrays). It is easy to show that under high loads a highly concurrent approach is better in terms of delay. At low loads we can expect lower delays with a parallel approach. More detail is presented on this idea in Chapter 4. [Gang94] notes that fine-grained striping is generally best employed in environments where transfer time dominates seek times. This implies that large video blocks must be transferred to maintain high efficiency in these arrays. Large blocks directly translate to large playout buffers. Coarse-grained striping does not impose this problem, since each video block is stored on only one disk. [Ng89] reaffirms this point but fails to present thorough quantitative results regarding the trade-offs between fine and coarse-grained striping in an interactive video

environment. The significant oversight of each of the above works is that they don't adequately account for the requirement of redundancy in disk arrays, which significantly affects performance.

Redundancy considerations present in RAID arrays add a level of complexity not considered in the comparisons discussed above. In Section 2.4.7 it will be seen that RAID 3 and RAID 5 systems use fine and coarse grained striping respectively, combined with redundancy to provide high capacity and throughput as well as system reliability. In Chapter 4, we develop analytical expressions, based on performability analysis, which accurately compare the trade-offs between fine and coarse-grained striping including the effects of redundancy.

There is actually a continuum of layouts between the limits of fine and coarse grained striping. In [Paek95] the authors present a discussion of a scheme referred to as multiple segmentation. This paper refers to fine-grained striping as balanced placement (all disks service each request), and coarse-grained striping as periodic placement (one disk services each request in round robin fashion). Multiple segmentation divides each video block into a variable number of segments for storage on the disk array. The number of segments dictates the degree of parallelism of retrieval. In an 8 disk array the segmentation can be 1 (coarse grained), 2, 4 or 8 (fine-grained). By considering this continuum the authors show that there is a trade-off between delay and interactivity. Fewer segments give higher disk utilisation, but also result in greater delays for interactivity. More segments decrease the disk utilisation (due to smaller block sizes) but reduce the worst-case delay for interactivity. Unfortunately a detailed analysis is not presented in this paper and the average case performance of the schemes are not compared. The authors suggest that the appropriate number of segments can be chosen based on the demand and interactivity requirements of a particular video object. They state that different videos can be segmented differently, but don't consider what effect this will have on the scheduling algo-

rithms used for each disk, the memory management routines, or on the call-admission control scheme required. Considerably more work is required before such a scheme can be deemed workable.

A similar scheme called Staggered Striping is presented in [Bers94]. This scheme is promoted primarily for systems where the bandwidth requirement of a single stream exceeds the bandwidth capability of a disk. By using several disks of an array in parallel, the aggregate bandwidth can be increased to satisfy these high bandwidth streams. In the vast majority of cases, however, the stream data rate will be considerably less than the capability of a single disk (3-6Mbps for MPEG compressed video, while a single magnetic disk can sustain bandwidths of at least 20Mbps, see Chapter 4) and as such these schemes are not considered further here.

An important consideration is the limit on the number of disks in each array. Currently this is largely dictated by the interconnection technologies used to connect the individual drives (eg. SCSI systems have a very limited bandwidth of 20MB/sec). New technologies such as ATM are, however, now being applied in the local environment [Hayt91] [Hayt93] [Chan95]. These scalable technologies will remove this constraint and as such it is assumed in this thesis that very large disk arrays (on the order of 100 disks) will be feasible in the near future [Mour96]. The size of such arrays will then be dictated by reliability constraints as discussed in Chapter 4.

Regardless of whether coarse or fine-grained striping is used, each disk in an array operates similarly. In either case, each disk has a set of requests to service within a given period of time to ensure that continuity requirements are met. In the following section we discuss methods to ensure that such constraints are guaranteed. The discussion is based on a single disk, but applies equally to the entire array.

2.4.3 Disk Layout and Scheduling

When attempting to serve interactive video from magnetic disks we must consider first how to place the data on the disk, and second how to schedule its retrieval. It soon becomes apparent that these two considerations are closely related (although the mapping is not unique), and as such we discuss them in combination in this section.

Disks are mechanical devices and as such request service times are difficult to accurately predict. The time to service a given request depends on the size of the request, it's location, and the current location of the disk heads. In order to serve interactive video we must ensure that requests are serviced within some time constraint to ensure continuity of playback to the customer. A number of techniques are available to guarantee that service deadlines are either deterministically or statistically guaranteed.

Magnetic disk drives typically have a considerably higher bandwidth than compressed video streams require (refer to Section 2.4.2). As such a single magnetic disk should be capable of serving several separate streams to clients. Even if a disk only stores one video object (eg. movie) it is required to be able to serve multiple instances shifted in time (or phases). In other words a single disk will be time-multiplexed among a number of streams.

It is infeasible to serve an entire movie to a client at the maximum disk rate. This will require massive buffers at the client, and cause long queueing delays to other requests. As such video must be stored and served in small "video blocks" each of which can be buffered at the client before playout. The next block should not be retrieved from disk until the previous block has almost completed playout.

Compressed video is inherently variable bit rate (VBR). As such a fixed block size will have a variable duration of playback. We thus

have a choice of Constant Data Length (CDL) or Constant Time Length (CTL) video blocks [Chan94b]. CDL storage uses a constant block size resulting in straightforward memory management and block placement on disks. The ensuing variability in playout time, however, means that CDL placement requires complex disk scheduling algorithms and cannot guarantee jitter-free video delivery [Chan94b]. CTL blocks vary in size making allocation more difficult, but playback for a fixed time, simplifying disk scheduling. For the fundamentally read-only environment of video-on-demand, CTL storage is generally considered to be preferable since it affords more efficient scheduling of the disk head movement. CDL, however, has the advantage of minimising fragmentation problems when data is frequently being modified. The trade-offs between CTL and CDL are well considered in [Chen95] and [Chan96a].

Regardless of whether CTL or CDL blocks are used, the block sizes will be relatively small in order to minimise the buffering requirements both within the video server and at the client. As such, a single disk will be multiplexed between requests on a fairly short time scale. There are a number of approaches to achieving this multiplexing, each of which will be discussed in some detail below. A good survey of disk scheduling algorithms for multimedia is presented in [Stei95].

2.4.3.1 Basic Approach

To retrieve several different blocks from a disk, the heads must seek from one block to the next before retrieval. The most obvious, and least efficient, technique for multiplexing disk heads among a number of requests is to move the disk heads to the location of each video block in order of request arrival (ie. effectively random order). Given a random set of requests, the disk heads will simply move to the correct location, read the video block and move to the next block. Figure 2.8 (a), illustrates the idea. Note that in this instance the video blocks are being served in no particular order (since request

order may change) from one round to the next. Hence we observe a large inefficiency both in terms of seek overhead and buffer requirements.

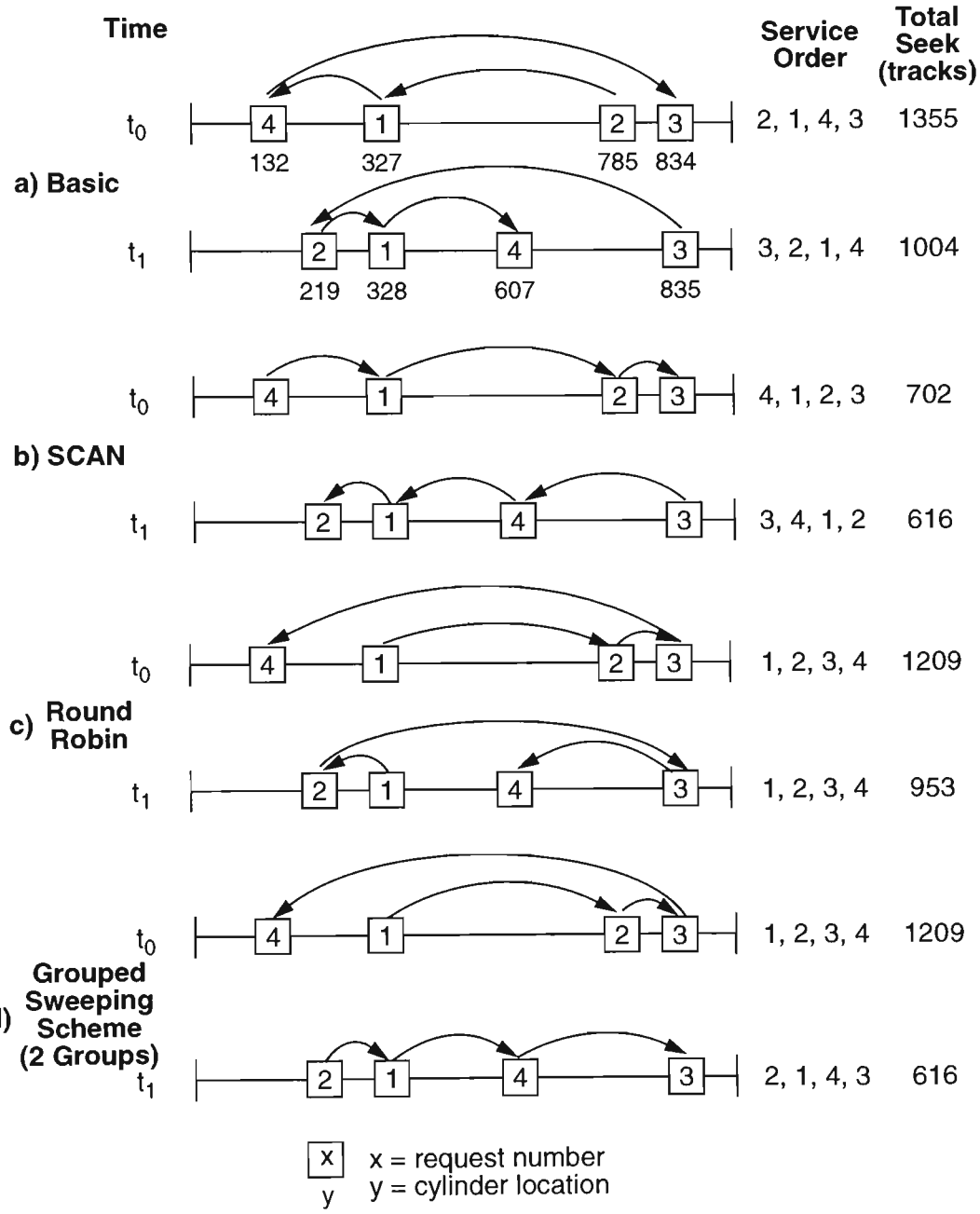


Figure 2.8 Illustration of various seeking schemes. a) Basic, b) SCAN scheduling to minimise seeking c) Round Robin scheduling to minimise buffering d) Grouped Sweeping Scheme minimises buffering and seeking jointly

It is clear that there are two aspects that require optimisation: seek time and buffer requirements.

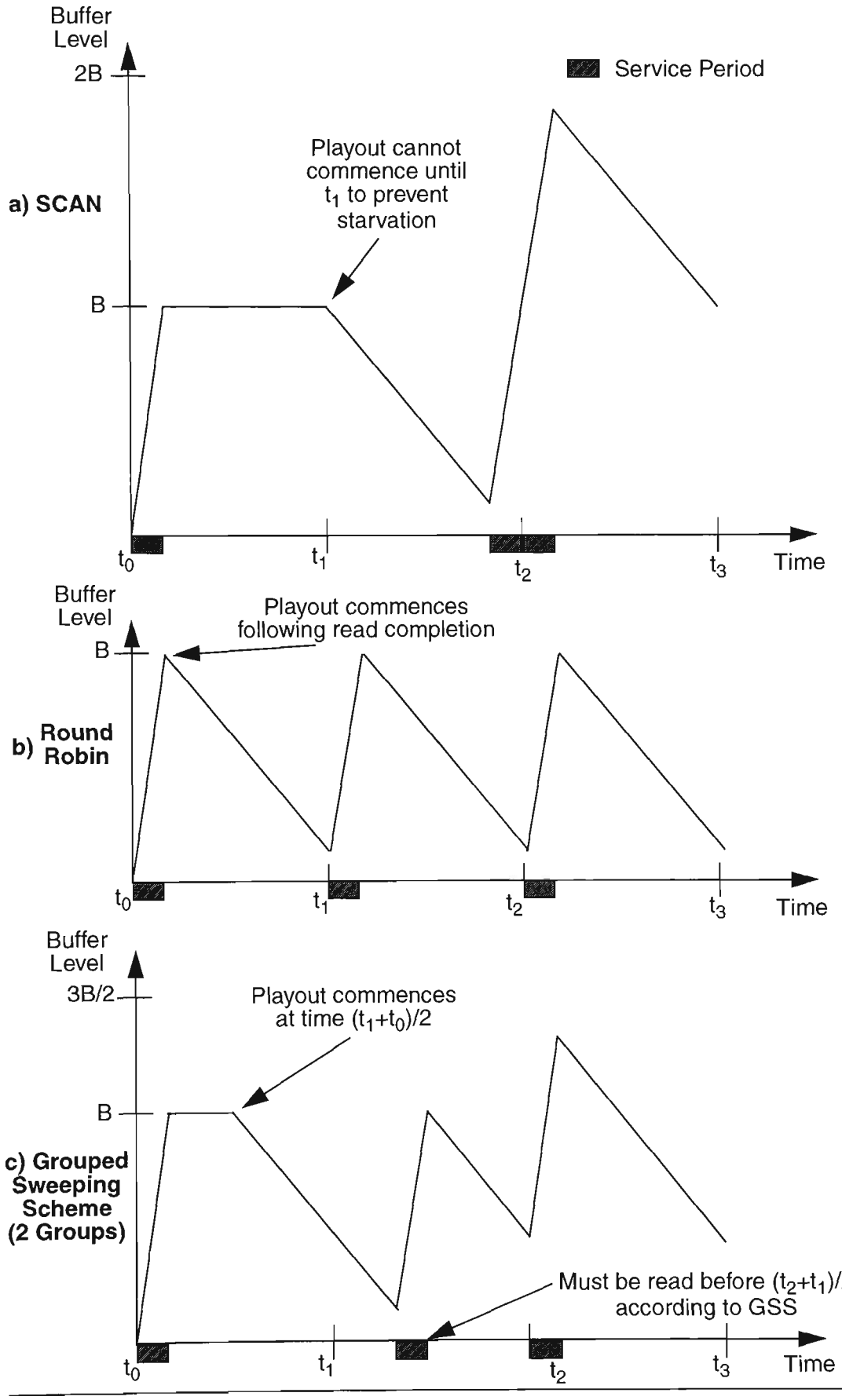


Figure 2.9 Buffer trajectories for a) SCAN b) Round Robin c) Grouped Sweeping Scheme (refer to [Toba93] for more detail)

2.4.3.2 Seek Optimising Schemes

These schemes service requests in cycles and aim to schedule the head movement so as to minimise the total seek time. The most common cycle based algorithm is the SCAN algorithm [Stei95] and variations of this (eg. C-SCAN [Wong94]). Using SCAN, the maximum total seek distance per round is limited to the number of cylinders on the disk. It is shown in [Wong94] and separately in [Oyan94b] that the maximum seek time occurs when the blocks to be retrieved are evenly spaced from the inner to the outermost cylinders. This is due to the concave relationship between seek time and seek distance measured in cylinders. The disadvantage of the SCAN algorithm is that a stream that was served first during one round may be served last during the next. Figure 2.8 (b) illustrates this idea, with stream 3 being served at the end of round 0 and again immediately at the beginning of round 1. This can occur regularly depending on the disk layout used, or with intelligent layout may be limited to when a user relocates to a different position in the video. To cope with this re-ordering of streams double buffering is required, ie a total of two times the video block size of buffering is needed per user [Wong94] [Sona95]. This buffer requirement is illustrated in Figure 2.9(a).

From Figure 2.8 (b) we also observe that the tracks in the centre of the disk are served more frequently than those at the outside. It is for this reason that placing popular material in the middle tracks as suggested by [Pang96], results in higher throughput since we are almost guaranteed to be crossing the middle tracks on every sweep.

The double buffering requirement incurred by serving streams in different orders in each service round can be removed by using schemes which maintain the order of service between cycles. These schemes will result in reduced buffer requirements, at the expense of higher seek overheads.

2.4.3.3 Buffer Optimising Schemes

Round robin schemes keep the service order constant during each cycle. This minimises the buffer requirement per stream, since play-out can commence immediately a data block has finished reading (see Figure 2.9(b)). The disadvantage is that seek schedules may no longer be optimal. In an absolute worst case the heads may have to perform a full stroke for every request. This will result in potentially very poor disk utilisation. Figure 2.8 (c) shows the seek schedule required by round robin schemes to keep the service order constant between cycles.

[Rang93], [Vin93], [Chan94b] and [Loug92] all assume worst case seek times between requests, which implies round-robin scheduling. None of these papers, however, presents it as being necessary for optimising buffer requirements.

Earliest-Deadline First is a variant of the round-robin algorithm adapted from CPU scheduling. As stated in [Stei95] this algorithm results in excessive seek times and makes it difficult to provide guarantees of service to individual clients. Adaptations of EDF have been proposed which alleviate this problem to some degree. These algorithms are discussed next.

2.4.3.4 Optimising both Buffer and Seeking

The Grouped Sweeping Scheme (GSS) [Yu92] aims to combine the merits of the cycle based and deadline based schemes. Requests are divided into groups where the groups are always served in order. The requests within each group, however, are served by the SCAN policy. This ensures that each block for a given stream will be retrieved at nearly the same time (minimizing buffer requirements) while also allowing efficient scheduling to be used within each group. The total seek time will always be less than or equal to that obtained by round-robin schemes, while the buffer requirement will be less than or equal to that of SCAN based schemes. How great the improvement

is in each case is determined by the number of groups. If one group is used the scheme degenerates to SCAN, while if there is only one request per group the scheme becomes pure round-robin. Interestingly, in the paper by Yu [Yu92], the recommended group size for large numbers of requests is one. This is because SCAN scheduling obtains the highest throughput from disk, which is required for a large number of streams. In this instance there is no advantage over the SCAN approach. An example seek schedule for GSS with 4 requests divided into 2 groups is shown in Figure 2.8(d). The worst-case buffer requirement for a single stream of a GSS group is shown in Figure 2.9(c). The buffer use shown agrees with the calculations of [Toba93].

SCAN-EDF (where requests are grouped together according to deadline and served by the SCAN algorithm within each group) has also been proposed as an improvement to the EDF scheme [Redd94]. It should be noted that this scheme operates precisely the same as the Grouped Sweeping Scheme, and as such the discussion presented above applies. Indeed the results produced by [Yu92] and [Redd94] for the two schemes are in good agreement. Although made under different assumptions, both analyses indicate that GSS/SCAN-EDF policies provide a slight advantage over SCAN policies alone in terms of buffer size required to served a given number of requests. They both have significant advantages over the standard round-robin or EDF schemes. [Toba93] also presents a discussion of the buffer requirements of GSS scheme and shows that the buffer requirements lie between those of SCAN and round-robin scheduling. This paper does not, however, go on to consider the effect that the GSS scheme has on disk throughput. It should be further noted that the Sorting Set algorithm proposed in [Gemm93] is also based on the same principle as GSS and SCAN-EDF.

2.4.3.5 Limiting Interaction

The schemes discussed above represent a continuum of approaches available to support interactive video from disk while minimising buffering requirements and/or maximising throughput. Truly efficient seeking and round-robin scheduling can both be achieved simultaneously, however, only if interactivity is not allowed. By appropriately placing data on the disk initially and admitting streams to an appropriate place in the service round (which may occasionally cause slight jitters for existing streams [Bers95]), the order of retrievals can be maintained for the entire duration of playback. Layout schemes to achieve this are straightforward and involve placing the video either contiguously or interleaved with others across the disk from outside to inside (or vice versa). A scheme proposed in [Birk95] takes this idea further by allowing elevator scheduling by placing one block in the outer tracks and the next block on the inner tracks of the disk. This scheme has the added benefit that it ensures a constant average data rate even on disks with multiple zones. [Bers95] uses a similar scheme to provide "Just-In-Time" scheduling which aims to retrieve a block only slightly prior to its playout. Berson et al. claim that this gives an order of magnitude decrease in buffering requirements over seek-minimising cycle-based schemes. This claim is unjustified by the paper and a considerably more detailed analysis is required to confirm this conclusion.

The above schemes although efficient, still incur a full stroke seek for every round of retrievals. By constraining the layout and admission of new streams this can be further improved. Several schemes propose the division of the disk surface into regions such that retrieval of blocks in each round only access a single region ([Oyan94b] [Ghan95b] [Cohe95]).

[Oyan94a] shows that such a scheme is a considerable improvement over the grouped-sweeping scheme in terms of the number of

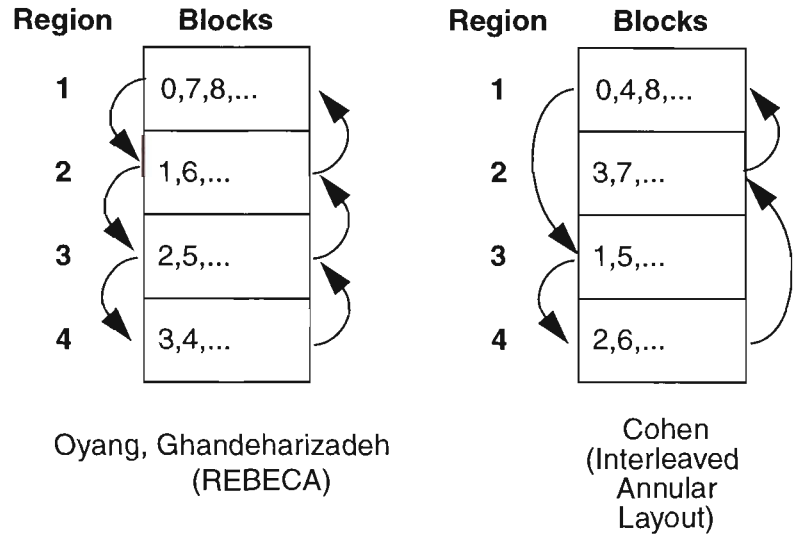


Figure 2.10 Differences between several region based block allocation schemes

streams supported for a given buffer size. Once again, however, such schemes only work if interactivity is not supported. [Cohe95] proposes Interleaved Annular Layout (IAL) whereby the regions are interleaved in such a way as to prevent the need for a long seek from the centre to the outside of the disk when the innermost region is reached. A similar effect is achieved by Region Based Block Allocation (REBECA) proposed in [Ghan95b] by placing the blocks within regions using a "folded" type of layout. The same technique is used in [Oyan94a]. The idea of region based block allocation is illustrated in Figure 2.10. which illustrates the difference between the proposals.

Taking the idea of region based block allocation to its extreme conclusion is a set of approaches where no seeking is involved at all. This method places different streams on the disk using block-division multiplexing across the disk surface. The disk head merely sweeps from the outermost track to the innermost, reading all the data in sequence. As the disk head sweeps (almost) deterministically across the surface block division multiplexing translates to time-division multiplexing of the outgoing streams. By spreading the data of a single stream across the disk with appropriate block and spac-

ing sizes it is possible to closely match the achieved throughput from disk with the required data rate of the video stream. The gaps created when one stream is placed on disk can be filled by other streams with similar requirements. Schemes based on this methodology are discussed in [Ozde96] [Yu89] [Rang93] and [Vin93]. We will refer to this layout policy as "block division multiplexing". A simple diagram serves to illustrate the scheme. Figure 2.11 shows the phys-

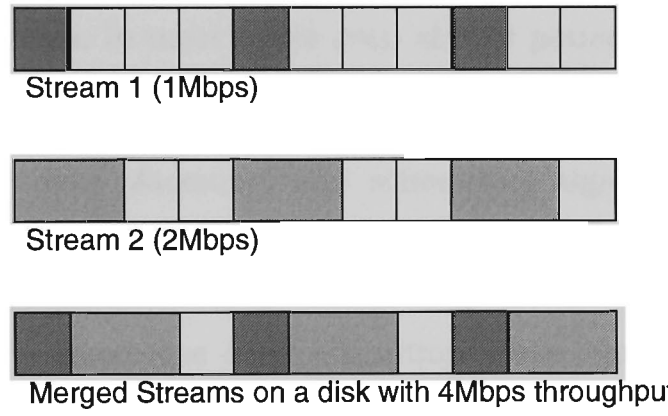


Figure 2.11 Illustration of block division multiplexing of video streams.

ical multiplexing of 2 streams encoded at rates of 1Mbps and 2Mbps, on a disk with a (low) throughput of 4Mbps. Efficient methods for achieving the merging of different streams are presented in [Yu89].

It should be noted that these block division multiplexing schemes are also useful if all streams in a merge group are required to be synchronised (as would be the case if audio and video streams were stored separately). Retrieval proceeds by starting at the outside of the disk and reading all the data (and distributing it to the appropriate clients) until we reach the end of the disk. This is effectively the simplest disk scheduling policy possible: fully deterministic, and is identical to the playback methods used on standard audio compact discs. This approach maintains the stream rate requirements and minimises disk seek overhead, since each seek is only one cylinder. However, the major drawback of these schemes is that interactivity is not permitted. In other words, once the retrieval commences for

any stream, there is no facility to pause or relocate since all other streams would also be effected. If seeking between block retrievals is permitted (as is the case in [Vin93]) then the properties created by the merge pattern are forfeited. This merge technique may still, however, be useful to reduce the problem of fragmentation which may occur with contiguous allocation.

The drawback associated with all of the above schemes that aim to optimise both buffer space and seek schedules is that interactivity is not well supported. In most cases even simple pause and resume or relocation functions can only be supported with long delays.

It is clear that data placement and scheduling algorithms must be used in combination to provide high throughput from disk arrays. By limiting the interactivity of users, very efficient schemes have been devised to maximise disk utilisation while minimising buffer requirements. Interactivity requirements of video servers necessitate the use of less efficient but more robust algorithms which allow relocation of streams without starvation of existing streams in a service round.

In summary, disk layout and scheduling policies have been a focus of recent literature. These policies have been aimed at removing the problems of the variable delay of disk seeks when serving real-time requests. A number of approaches have been recommended, all based on existing scheduling algorithms. It is now possible to place video on disk and retrieve it with high efficiency if interactivity is not required. However, providing interactivity requires the use of less efficient policies which effectively increase the load on the video server and therefore also increase total system cost. Without a detailed understanding of user requirements it is difficult to determine the level of support required for interactivity. Papers to date have been forced to make simplifying assumptions regarding this.

For the purposes of this thesis, a round-robin based scheduling scheme is generally assumed based on CTL blocks which correspond

to an integer multiple of a GOP. Given these scheduling and layout policies, a video server needs mechanisms to perform call admission control on new streams. These admission schemes should aim to maintain a balanced load in the server and to minimise delay to new requests.

2.4.4 Call Admission Control, Load Balancing and Delay

When a new request arrives, the video server must determine whether it can service it without disrupting any of the requests currently in service. If it can, the call is admitted and playback proceeds, else the call is blocked or queued until resources are available. This process is termed Call Admission Control (CAC). In a video server it is likely that a user will tolerate some amount of delay before playback starts. If necessary the server may delay a request for some time before service begins, otherwise the call must be blocked (rejected).

Call-admission control in telecommunication networks is extremely well studied. However, in the case of interactive video servers the situation is sufficiently different to warrant re-examination. Traditionally, network CAC has relied on a statistical description of the traffic (eg. Peak-Cell Rate and Mean Cell Rate) in order to give a statistical guarantee of service (eg. small loss probability). In a telecommunications network, future traffic loads are difficult to accurately predict. Even individual clients cannot be aware of how much traffic they themselves will generate in the future. It is for this reason that only a few parameters are used in attempting to characterise each traffic source at call admission time. In the case of interactive video, however, the situation is considerably different. Since a video server stores all of the data that is to be transmitted, it has detailed future knowledge of the load that is to be placed on it. As such it would seem reasonable to assume that a video server can potentially perform much more aggressive admission control than has been possible in other data networks.

Early CAC schemes proposed for interactive video systems were based on the existing idea of using a statistical profile of the traffic to determine overflow probabilities. These schemes are effective because the statistics can be quite detailed (full distributions being easily determined) and are known to be accurate. Using these statistics in combination with a model of disk drive performance, overflow probabilities can be calculated. Should the total overflow probability of the existing streams and the new admission fall below some threshold then the new stream is admitted. Statistical call-admission control schemes have been proposed by numerous authors. Often these schemes assume some average or worst case statistics of disk seek and service time for each request. Papers by [Rama95] [Chan94b] [Vin93] [Gemm92] and [Redd94] all fall into this category of worst-case admission control. [Chan94b] provides a thorough consideration of the statistics of MPEG encoded VBR video and provides computationally efficient schemes for ensuring a given loss rate for several priorities of customers. By allowing several priorities of customer (each with different QoS requirements) the service scheme can gracefully reduce service to clients that are more tolerant of loss. Such a technique is useful when FF and REW interactions by a user cause an increase in load on the server (see Section 2.4.5). A priority scheme also allows the server to admit slightly more customers with low QoS guarantees than a single-priority admission algorithm could. One downfall of Chang et al's approach, however is that they also only consider worst case disk seek times although this does prove to be a safe upper bound.

The paper by [Vin94a] improves on this scheme by individually considering the statistics for each separate stream. Also they model the seek time as a (simple) distribution rather than the average or worst case. The results show that this statistical scheme gives much better performance (in terms of clients admitted) than its worst case counterpart. Vin, however, does not allow multiple priorities of clients. It would seem that a combination of the two schemes would form an

efficient statistical call-admission control scheme. Utilising even more detailed data about each video object, however, has the potential to lead to even more efficient, deterministic, admission techniques.

The video server has total knowledge of the bit rate requirements of all the streams it is requested to serve. By using this more detailed temporal information instead of just the statistics of the trace, it would seem reasonable to expect higher utilisations and admission rates than are possible with the statistical approach. Such an approach is referred to as deterministic call admission control, since the guarantees provided are absolute. Several authors have recently proposed deterministic call admission control schemes based on this idea [Ryu96] [Lau95a]. Such methods may, however, provide poor support for interactivity since each interaction (or pause/restart) is treated as a new call admission and as such is subject to a CAC test. A detailed deterministic CAC scheme is presented in [Neuf96] but no results are presented regarding its performance. It is clear that the improvement gained by using deterministic admission will be closely related to the characteristics of the video data being stored and of the storage subsystem itself. A recent paper by Chang and Zakhor [Chan96a] uses real MPEG compressed video streams to study the benefit of deterministic admission control schemes. The paper indicates that a 10-20% increase in the number of streams admitted is possible, with only a slight (5-7%) increase in interactivity delay.

The primary downfall of the existing CAC schemes (including [Vin94a] and [Chan94b]) is that they often don't consider the individual resources in a video server before admission. Specifically they tend to admit streams to a given disk group provided that the whole group is not serving the maximum number of streams. This method is sufficient in fine-grained striping groups where all disks co-operate on all requests. In coarse-grained striping groups, however, we must consider the load on each disk individually before admitting a stream. It may be beneficial to delay or block admission in order to

maintain a balanced load across the array. In Chapter 6 we utilise similar techniques to those described above to determine limits on disk throughput, before using these limits to investigate the benefits of selectively delaying admission of certain requests. A scheme termed "Predictive CAC" is developed which is shown to provide significant advantages in terms of admission delay, without requiring any additional server resources.

2.4.4.1 Load Balancing

The idea of load-balancing has a number of meanings in the context of interactive video networks and servers. At the highest level, an interactive video network consists of a large number of servers. It is important that viewer load is shared evenly across each server. As already mentioned, several authors have investigated this problem ([Loug94] [Fede94] [Nuss95]), and it is further discussed in Chapter 3. It is also important, however, that load is balanced across storage subsystems (eg. disk arrays) within a server and across devices (disks) within each subsystem (array).

Each individual video server will consist of several (perhaps many) disk arrays each storing different movies and each disk array may consist of a large number of disks. Once again it is important from an efficiency perspective, that each of these disk arrays is equally utilised. If a storage hierarchy is used, the situation is even more complex. Several papers deal with the problem of ensuring a balanced load *between* arrays, [Litt95] [Dan94a] [Wolf95] [Barn96e].

[Litt95] draws the useful (although obvious) conclusion that a system operates most efficiently if all storage devices (disks or disk arrays) have an equal probability of being accessed. The authors suggest that movies should be stored on individual disks, and replicated to meet the throughput requirements as necessary. They state that the problem of allocating movies to disks is NP-hard, but make no attempt to derive any form of solution to the problem. Also, the

authors fail to consider the benefits of disk striping in order to avoid the extra cost incurred by video replication.

[Dan94a] is one of a series of papers by Dan et al. This paper proposes a scheme called the Dynamic Segment Replication Policy. Given an initial configuration of movies on disk arrays, this scheme aims to maintain a balanced load by dynamically shifting popular movie segments to lightly loaded arrays. The authors compare this scheme to one which uses static movie placement and show that the dynamic scheme can provide considerable improvement. There are, however, a number of issues that are unclear from the paper. First, it is unclear what penalty the authors assume the copying of segments incurs to the load on the system. Specifically, in a RAID based disk array, write operations are considerably more expensive than read operations and this may not have been accounted for in the simulation model used by Dan et al.

Second, the initial placement technique used for the static policy is open to question. The static policy relies on the load being well-balanced when movies are initially allocated to disks, and its performance is very sensitive to this placement. The authors have used the intuitively appealing idea of "folding" the ordered set of movies onto the disk arrays. Unfortunately, for the Zipf distribution which is assumed to model popularity, this does not result in a particularly well balanced system. In fact for the parameters chosen by the authors, the least loaded disk array has just 70% of the load of the most loaded array, while the mean load is only 80% of the maximum. It is reasonable to expect that the static policy will not perform particularly well under these conditions.

A paper by Wolf et al. [Wolf95] examines both static and dynamic schemes for load balancing between arrays, in a scheme called "DASD Dancing". The authors use techniques based on graph theory to allocate (statically) movie copies to disk arrays in such a way that load is generally well balanced and so that, should load imbalance

occur, load can be shifted (or danced) from overloaded to underloaded disk arrays. By creating a highly connected graph of disk arrays (by ensuring that many arrays store copies of the same movies) load can be easily moved from one array to another during playback (dynamically). Simulation experiments are used to demonstrate that the proposed scheme does indeed lead to improved load balance (over greedy or single copy schemes) and that this in turn leads to a higher system throughput.

The method proposed is quite complex, and although successful is based on a number of assumptions. Wolf et al. assume that all movies require the same storage capacity and as such that all disk arrays can store the same number of movies. This implies that all movies are the same length and encoded to the same bit rate. Also, the maximum degree of disk striping (the number of disks in each array) in this study is limited to 8. Other authors assume that disk arrays of tens or hundreds of disks will be required to efficiently meet customer demand [Mour96]. The restriction of only 8 disks per array leads to large amounts of duplication being required to serve the popular movies which in turn is what leads to the improved performance of the proposed "DASD Dancing" scheme. Obviously this duplication of titles results in wasted storage capacity, when the duplication is actually only being used to gain an increase in bandwidth. With larger disk arrays duplication is rarely required and the scheme proposed by Wolf et al. will provide no benefit.

In Chapter 5 an efficient heuristic is developed which requires no duplication of movie titles, and guarantees to meet storage and throughput requirements for a large user population.

The problem of balancing the load *within* a disk array is not well considered. In a fine-grained array this is no problem, since all disks move synchronously to serve requests in parallel, and as such are perfectly balanced. In a coarse-grained disk array, however, call-admission control schemes must be used to keep the load balanced

across the disks in the array. We discuss this issue in more detail and introduce schemes for maintaining a balanced load in a coarse-grained disk array in Chapter 6.

2.4.5 Support for Interactive Services

To be widely deployed, video servers will be required to support at least elementary interactivity. We regard the very basic interactivity requirements as pause, restart, and relocate. The next level of support which will be required for many applications is variable speed playback in both forward and reverse directions. To mimic VCR technology a single speed fast play (FF) and fast reverse (REW) will suffice. Ideally, however, a range of speeds in both forward and reverse directions would be available. To date most of the literature has focused on providing simple fixed-rate fast-play and fast-rewind schemes.

The appearance of the current "shuttle search" (fast play) feature on VCR's is merely an artefact of the technology used to provide it. As such, attempting to mimic this appearance with a completely different technology may not be feasible. The schemes that have been proposed to deliver N times fast play to date can be categorised as follows [Shen95]:

- **Retrieve frames at an increased rate [DS94]**

These schemes increase the load on the video server, the client decoder and the network as well as increasing the buffering required in between [Budd95]. An N times speed-up results in N times the load on all of these resources. Also the client decoder may not be able to decode compressed video at the higher rate. Although this scheme is the most obvious it is clearly the least efficient and will not be supported by large-scale video servers.

- **Retrieve every Nth frame [Shen95]**

By dropping the frames between every Nth frame and maintaining the same nett frame rate, the client decoder and network perceive no difference between the fast-play and normal stream. This scheme will also present a very natural appearance to the customer.

Retrieving every Nth frame from the video server will, however, increase the server load considerably depending on the data layout strategy used. With only small amounts of data being read from each video block the seek time required is much larger than for a normal play request which can be satisfied by a single contiguous read. Also if a compression scheme like MPEG [LeGa91] is used, interframe dependencies will exist. This means that a given frame cannot be decoded without information from neighbouring or nearby frames. As such only fixed rates of fast-play will be supported using this scheme, and the load on the server (and network) will be further increased due to the fact that I and P frames are considerably larger than B frames (refer to Section 2.2.3.1).

[Shen95] overcomes these problems by storing the normal playback stream partitioned into three substreams. This partitioning removes the frame interdependencies and reduces the resolution of the fast-play stream to maintain the same bit rate even though only I and P frames are being transmitted. Thus, if a user is in fast-play mode, the server retrieves a number of small blocks (just the base sub-stream), while in normal playback mode one large block is retrieved per cycle. The authors develop an analysis which (although in disagreement with a simulation) indicate that load is not effected very much regardless of the number of streams in fast-forward mode.

Nagpal and Kanakia in [Nagp96] describe a system which transmits only I frames and maintains a constant bit rate by reducing the number of frames per second (rather than the resolution as proposed by Shenoy et al.). The authors state that this is directly analogous to the fast-search functions found on laser disc players which

have been shown to be acceptable to users. The paper does not consider how this style of frame skipping would effect the load on the video server or how it would be supported by the client.

- **Retrieve every Nth Group of Pictures [Chen94a]**

[Chen94a] originally proposed a scheme whereby every Nth GOP is retrieved and played back normally. Since a GOP generally corresponds to about $^1/_2$ to 2 seconds of video this results in a somewhat "sporadic" fast-play. Chen et al. develops two schemes for supporting such interaction and performs visual experiments to suggest that this style of fast-play is visually acceptable to the user.

This style of fast-play is very different to what is currently seen in VCR technology, and the user response to this is currently open to question. In [Nagp96] the perceptual effect is described as being highlights rather than fast motion. However, it has significant advantages in that it supports various rates of fast-play without increasing storage or bandwidth requirements on the server. [Budd95] develops methods for ensuring that load remains balanced (in the long term) across all disks in an array even during fast play using this "sequence variation scheme".

- **Encode separate streams [Saka96]**

By encoding and storing separate streams for fast-play, reverse-play etc. we can easily switch the video server to the different streams in response to commands from the user. With appropriate coding parameters, the stream bit rate, and hence load on the server can be kept constant for all streams. The drawbacks of this approach are that extra storage overhead is required and variable fast-play speeds are not supported.

This method seems to be quite straightforward for providing high-quality fast-forward. For this reason it is currently being used in prototype and deployed systems, but is not generating much interest

in the research community. Chapter 6 assumes this implementation of interactivity functions when considering call-admission control.

2.4.6 Techniques for Load Reduction

It is clear that interactive video servers will be required to source extremely high data rates into the core network. It is, however, possible to reduce the load placed on the server. By combining several streams together to be served as one by the server and then multicasting them across the network to multiple users, considerable cost savings at the server may be possible. In its simplest form this idea is most commonly known as Near-Video on Demand. As discussed in Section 2.2.1 such a service provides limited interactivity (pause and resume at a granularity in the order of minutes).

It is possible to reduce server load while still maintaining full interactivity for streams that require it. Three techniques have been proposed to serve several customers with a single multicast stream [Golu95]:

- **Bridging**

[Kama94] and [Dan94c] both propose this technique which revolves around buffering individual requests' data for a short period and serving closely following requests from this buffer. If a group of streams are all temporally close together, then only the first stream is read from disks with the remainder of the group being served from buffer. [Dan94c] develops efficient algorithms for such a scheme and demonstrates their effectiveness through extensive simulation. A cost analysis also reveals that small amounts of buffering can be justified in terms of the total system cost. This cost analysis, however, assumes unrealistically high costs of disk drives and low costs of RAM. If this imbalance were corrected it would be unlikely that the use of RAM could be justified even with these intelligent caching schemes.

[Nuss95] also proposes the use of bridging on a network wide basis by caching a small portion of programs at a head-end server.

- **Batching**

[Dan94b] proposes the use of batching where an initial user request may be delayed in order to allow several streams to use the same video instance. By incurring such a delay the likelihood of a user reneging is increased, but this is minimised by selecting an appropriate batching interval. Contingency streams are reserved in the server to allow a user to split from the current batch when interactivity is required.

The paper by Dan et al. only supports pause and resume interactivity. Fast-play and other interactive features are not discussed. Also the authors assume that a contingency channel will be available for use by any stream. In reality contingency channels will have to be allocated for each disk array or individual disk, which will increase the number required considerably.

Similar schemes are discussed in [Alme96] and [Jada95] with similar limitations.

- **Piggybacking**

A final technique for combining streams together is called adaptive piggybacking [Golu95]. This scheme relies on the observation that viewers will not notice a speed-up or slowdown of a video stream provided it is within +/- 5% of the nominal rate. As such if two streams are close together, the leading one can be slowed down slightly and the trailing one can be sped up until the two streams meet. At which time the server is only required to source one stream which is then multiplexed to the customer.

The slightly faster and slower streams will, however, require either specialised encoding hardware to generate in real-time or will need to be stored separately, incurring an expensive storage overhead.

Although Golubchik et al. show that this mechanism can indeed reduce the load on a video server, it is far from being mature and requires considerably more investigation.

In general, reducing load in a truly interactive video server relies on a fairly low level of interactivity for each user. The studies to date assume this low-level of interactivity although market surveys are not available to reinforce this assumption. For the remainder of this thesis we assume that fully interactive video is supported by the video server without any of the load reduction features mentioned above.

2.4.7 Reliability of Large Disk Arrays

Despite the number of papers discussing the use of disk arrays for interactive video, the number that deal with reliability issues is surprisingly small. Most work merely refers the reader to standard RAID literature (eg. [Patt88] [Chen94b]) without considering how RAID architectures really impact the performance of interactive video systems.

Originally, RAID systems were proposed to give high data survivability for critical applications where data loss was not tolerable. In interactive video the requirement for redundancy arises from a different perspective. Interactive video servers must be highly available. In other words they must be able to serve a maximum number of requests for a high percentage of the time they are in operation. Losing data is not actually a concern since all data is assumed to be held on archival storage (eg. tape) anyway and can always be restored from there should data loss occur. In Figure 2.12 we show the various RAID levels currently defined. For a detailed discussion of each level we refer the reader to [Chen94b] or for a more readable and recent introduction to [Frie96].

The standard RAID systems maintain throughput following disk failure to a varying extent. Although some papers have investigated the

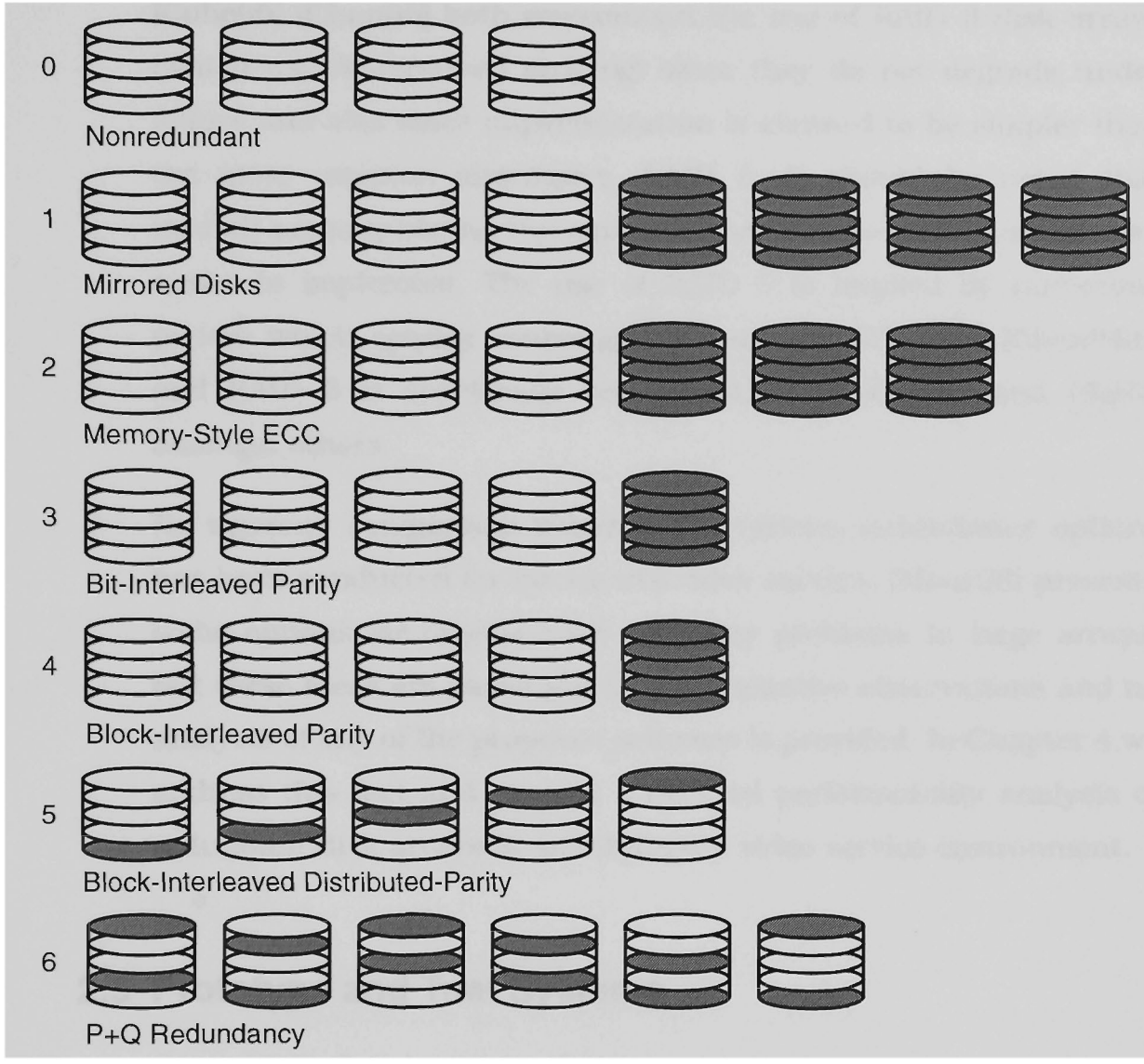


Figure 2.12 Various levels of RAID arrays (from [Chen94b])

performance of RAID systems in failure mode [Munt90] [Ng92], the literature to date has not really considered the effect that this has on video server design, with its unique workload. The two levels of RAID that have generated most interest are levels 3 and 5. Both of these provide a parity disk to survive single disk failures. The difference between the schemes is that RAID 3 implements fine-grained striping while RAID 5 uses coarse-grained striping. The discussion in Section 2.4.2 implies that RAID 5 may be preferable in a fully operational state. When degraded performance is accounted for, however, the situation becomes more complex. Indeed, numerous contradictory references regarding this issue appear in recent publications.

[Cohe95] [Chan95] both recommend the use of RAID 3 disk arrays (which use fine-grained striping) since they do not degrade under failure and also since implementation is claimed to be simpler than the most common alternative, RAID 5. It should be noted that [Seo95] actually claims the opposite: that coarse-grained arrays are easier to implement. The use of RAID 5 is implied by numerous papers which employ coarse-grained striping [Shen95] [Chen94a], and RAID 5 is specifically recommended by [Orji96] and [Ng92] amongst others.

No rigorous comparison between the various redundancy options has been conducted for interactive video servers. [Mour96] presents some options for dealing with reliability problems in large arrays, but these ideas are based purely on qualitative observations and no analysis of any of the proposed schemes is provided. In Chapter 4 we address this fact and present a detailed performability analysis of redundant disk arrays in an interactive video service environment.

2.5 Prototype and Trial Systems

Current implementations of interactive video servers can be divided into two categories: laboratory prototypes and field trials.

Laboratory prototypes are generally unrealistically small and built solely to test proposed schemes and architectures. Field trials, however, are constructed on a much larger scale and are currently being deployed all over the world. The primary purpose of these is to assess the customer demand for interactive video services and test different products as well as developing appropriate pricing and marketing strategies.

2.5.1 Laboratory Prototypes

Laboratory prototypes have a definite purpose in that they account for all the factors of the physical system often ignored (due to the dif-

ficulty in accurately modelling them) in even detailed simulations. At the same time, prototypes are often unrealistically small and as such the trends observed in these systems cannot be reliably extrapolated to a large-scale system.

Numerous prototype systems have been constructed by various researchers in order to test algorithms and techniques proposed. Although we won't review these schemes in any detail here, we refer the reader to the following papers for more details: [Genn95] [Rama95] [Gemm94] [Chan95] [Pang96] [Saka96] [Lin96a] [Crut94] [Loug92] [Fede94] [Chen94a].

2.5.2 Publicly Deployed Field Trials

Recent popular literature contains a number of articles concerning field trials of interactive video services. Refer to [Perr96] for a list of ongoing trials. These trials have the common goal of trying to ascertain the likely market interest and required pricing structures for interactive video services. Although little information is publicly available regarding the success of these trials, one thing is becoming clear. Customers are not willing to pay very much for what they perceive as an enhanced version of cable TV. One survey returned the following results [Ano95]:

- Movies-on-demand type applications will be by far the most popular use of interactive video servers for the foreseeable future.
- Customers will only pay between $30 and $50 per month for access to these services.

This indicates that it is reasonable to focus on the movie-on-demand application of interactive video for the foreseeable future, and also that interactive video services must be built as cost-effectively as possible in order to return a profit. Both of these points are adopted to guide some of the directions of this dissertation.

Very few technical details regarding these trials are publicly available. It is clear however, that the trial roll-outs have been done at great expense; considerably more than could be justified in a full-scale deployment. As such considerable development must take place before wide-area commercial deployment is possible. Effectively this means that the problem of providing interactive video over a broadband network has not been solved in a cost effective manner. Hence we see the current high-level of research interest in this issue.

2.6 Relevant Standardisation Work

As with any area of telecommunications, standardisation of interactive video network architectures is essential. Numerous standardisation bodies are actively working on various aspects of interactive video systems. Perhaps the most influential is The Digital Audio-Visual Council (DAVIC). DAVIC was formed specifically to consider end to end issues related to digital audio and video and seeks to reuse standards from other bodies wherever possible, in order to streamline the standardisation process. DAVIC released version 1.0 of its standard document in 1995 [Digi95]. As with any standard this document is comprehensive and detailed and seems to be widely accepted among manufacturers. DAVIC 1.0 lists a range of functionalities that must be supported by any DAVIC compliant system. For example, interactivity with VCR like control is required, including fast and slow play in both forward and reverse and pause and random skipping within a video object. The actual nature of these facilities, however, is not specified in the standard.

Since this thesis is primarily concerned with implementation issues and optimisations, standards are not of particular importance. As such we won't provide a detailed review of any of the standards here. We will however, refer to them through the course of the thesis where necessary.

2.7 Summary

It is impossible to cover all the issues related to interactive video service provision in a single review. In this chapter we have tried to identify the major efforts and indicate where this thesis provides new contributions. Some of the contributions of this project are extensions of earlier work, while others consider new issues that have not been specifically considered before. It is not our aim to repeat the perfectly good work of others, instead their work is re-used where possible and extended or generalised where necessary.

This chapter has provided a critical review of existing efforts in the provision of interactive video. Throughout the course of this discussion a number of deficiencies in existing work have become clear. This dissertation does not attempt to address all of these. Instead we focus on some of the important issues that occur at different levels of interactive video network and server design. The aim is to develop and validate mechanisms for ensuring that interactive video networks can be deployed cost effectively and with a high degree of reliability. The next section summarises the main shortcomings of the current literature with respect to this dissertation. The items addressed by this dissertation can be found in the list in Section 1.3.

2.7.1 Deficiencies in the Existing Literature

- The consideration of appropriate network architectures have used unrealistic assumptions regarding server cost, network architecture and workload.
- Cost analyses use widely varying component cost estimates often apparently chosen to support the argument being presented.
- There is no consistent understanding of a minimum set of requirements to be supported by a video server.
- No framework exists for the comparison of the different proposals for interactive video service.

- Accurate models of video object popularity and its change over time have not been developed or validated.
- A detailed comparison of disk striping techniques especially with reference to reliability issues has not been performed.
- An initial placement policy for balancing load between disk arrays has not been developed. This is despite several publications which point out the importance of this load balancing.
- Call-admission control schemes which maintain a balanced load within a coarse-grained disk array have not been developed.
- A complete design procedure for interactive video systems has not been presented.

3. Interactive Video Network Design

Men occasionally stumble over the truth, but most of them pick themselves up and hurry off as if nothing happened.

- Winston Churchill

3.1 Introduction

A top-down investigation of interactive video networks must necessarily begin with the network configuration. This chapter examines the network architectures and compares the options for server configuration and placement in a wide area network. Specifically, distributed and centralised storage architectures are compared under a realistic model of storage and network cost. The chapter also presents efficient caching algorithms which enable a distributed approach to storage to be most cost-effective in terms of both storage and bandwidth expenditure.

Section 3.2 considers the network architecture appropriate for interactive video and the costs of various components of the network. From this examination, Section 3.3 focuses on server costs and develops a cost model for disk based video servers. A novel hierarchical disk based server architecture is proposed in Section 3.4 and compared with the homogeneous approach assumed earlier. Section 3.5 uses the server cost model to analyse the cost of distributed and centralised approaches to storage. A distributed approach relies on the use of caches to store the most popular movies close to

customer populations. Algorithms for maintaining cache currency are developed in Section 3.6. The conclusion presented in Section 3.7 reveals that a distributed approach can be expected to be the most reliable and cost effective method of providing interactive video services to a large user population.

3.2 Network Architecture and Costs

Chapter 2 presented a graphical representation of a generic network architecture (see Figure 2.3). Any number of technologies and topologies could be used in such a network. The distinction between core and access networks is however, always present. The AT&T integrated consumer video services platform, for example, uses an ATM backbone in the core network and either ADSL or HFC technology in the access network [Blah95]. The access network is connected to the core network by way of an appropriate gateway (termed a Front End Server in Figure 2.3). A similar architecture is presented in [Chan94c] which uses a SONET ring with add-drop multiplexers in the wide area network. Here Video Dialtone Gateways form the access point for the customer into the core network. Due to infrastructure costs it is clear that core and access networks will rely on fundamentally different networking technologies for some years to come [Bure95]. The actual topology of either the core or access network is difficult to generalise. Stars, trees, meshes and rings are all viable topologies for a core network organisation, while a wide tree based structure would be used for HFC access networks and a star configuration for ADSL based access networks.

Due to the difficulty in making assumptions regarding network topologies, the only assumption made here is that an interface point exists between the core and access networks. No inferences are made regarding the actual technology or topology used in either the core or access network. Since no specific core and access network architectures are assumed it is impossible to accurately estimate the

bandwidth cost incurred by a particular viewer load on these networks. It is clear however, that bandwidth costs will be minimised by reducing the quantity of traffic in the core network. This can be achieved through the appropriate use of video buffers in the Front End Server. As discussed in Chapter 2 the point of interconnect will require considerable functionality and as such it is surmised that it would be feasible to incorporate the functionality of a small video server at such a point [Chan94c] [Li96].

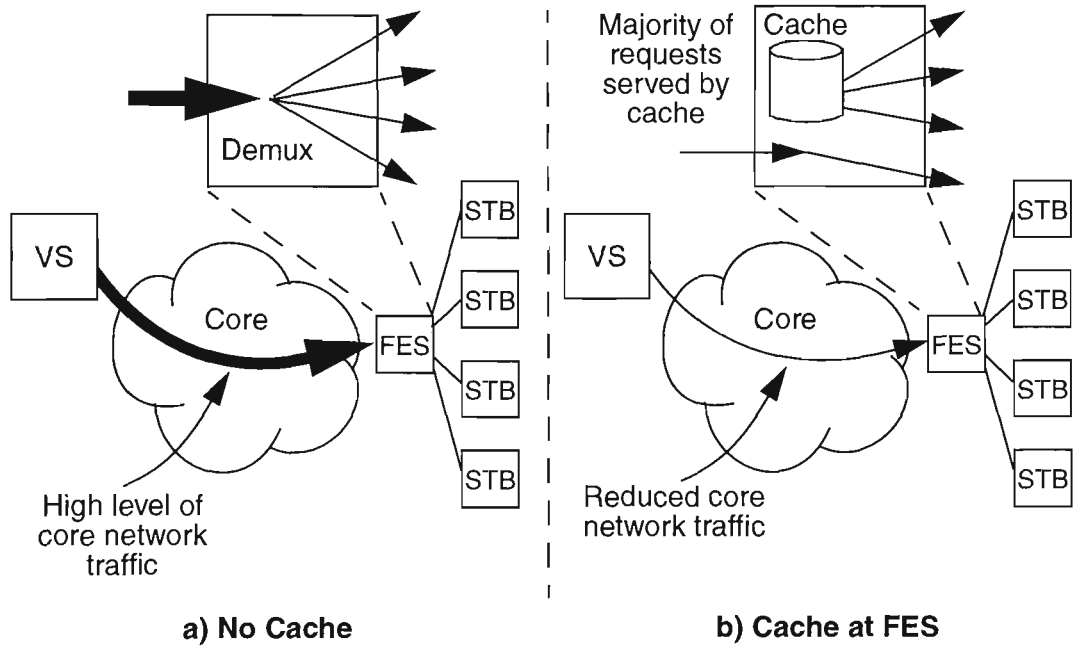


Figure 3.1 Bandwidth savings in core network by using caching at the front-end server

Since network and bandwidth costs are highly dependent on the architecture of the physical network it is desirable to remove such factors from any comparison of interactive video architectures. Here distributed and centralised approaches to storage are compared based purely on the cost of storage, with the overriding assumption that (regardless of network topology) bandwidth costs will be minimised by the most highly distributed approach to storage as indicated by Figure 3.1[1]. It is for this reason that bandwidth costs do

1. Note that in this thesis, the term "distributed storage" refers to locating storage close to the customer populations, at the FES's. Thus, highly distributed storage would see large servers at each FES.

not need to be studied in detail. Although not immediately apparent, it will become clear that a distributed approach minimises not only bandwidth costs but server costs as well.

Apart from network and server costs, the other major cost of providing interactive video services lies in the customer premises equipment (CPE). In most cases, the CPE is assumed to consist of a simple Set Top Box (STB) which is responsible for interfacing to the network and decompressing digital video for display on a standard TV. The issues involved in STB design do not significantly effect the cost of the network itself and so these can also be omitted from the cost comparison presented here.

From the arguments presented above, this chapter proceeds by developing a detailed model for server cost and then compares interactive video architectures using this cost model. This approach has the advantage of avoiding the need to make assertions regarding network architectures, while still drawing useful conclusions regarding optimal design methods for interactive video systems. In the following sections models of server cost are developed and validated.

3.3 Server Cost Model

It should firstly be noted that the term video server as used here refers both to the dedicated video server in the core network, and the smaller servers used as caches in the FES. Similar physical architectures would be used in each case, and as such, the same cost models can be applied.

An interactive video server is a device capable of storing and serving real-time compressed video data. In order to compare various methods of dimensioning and placing such video servers in a network, an accurate server cost model is required. Precise determination of costs for a particular video server does, however, require detailed knowledge of the server architecture. Making detailed assumptions

regarding server design will, however, reduce the applicability of our cost model, which is clearly undesirable. Although the implementation of a video server will vary from one design to the next, all will require some form of mass storage to meet the intensive multimedia requirements already discussed. Several recent papers [Chan94c] [Kova94] have shown that storage costs constitute the major cost of videos servers. For this reason our model of server cost is based purely on storage costs with associated costs assumed to scale closely with storage costs. By making this assumption, it is possible to develop an accurate and yet widely applicable model for the cost of a video storage server.

The approach used in this chapter differs significantly from those in the literature [Bisd95] [Nuss95] [Papa95] [Yosh96]. Most importantly, the cost model developed here is based on a physically realisable hardware architecture, but is not so specific as to be limited in its applicability. Previous efforts at modelling interactive video systems have not used cost models based on physical implementations. As such the validity of these models is open to question and difficult to prove.

Two recent papers illustrate this point graphically. A recent work, [Papa95] assumes that storage in large servers is "multiplexed better" and as such the unit cost of storage is lower in larger servers. Although this seems reasonable, the authors make no effort to quantify this difference nor to show the assumed costs are realistic. Following this assumption, costs per unit of storage are then assigned arbitrarily to servers at various levels, complying only with the simplistic rule that storage is cheaper per unit in larger servers.

In [Nuss95], it is assumed that the opposite property is true of storage costs. That is, costs become greater per unit as higher demands are to be supported at a single server. Once again, this assertion is not based on any physical storage model and so is difficult to justify. In [Nuss95] a parameter is assigned to control how quickly costs

increase with capacity, and the lower limit assumes a linear increase in total cost with capacity (that is, unit cost is constant, independent of server capacity).

The model derived in this chapter is based firmly on a physically achievable implementation of a video storage server. Although considerably more detail is required when formulating a model based on a physical implementation, it is clear that such a solution is much more readily justified than the arbitrary assertions presented in previous literature. Before continuing with the model derivation Table 3.1 defines the symbols used in the remainder of this chapter.

Table 3.1 Symbols used in cost model

Symbol	Definition
N	Peak number of streams to be served
K	Number of video objects (movies) to be stored
S	Storage required by a single movie (GB) (may be subscripted)
C	Capacity of a single disk (GB) (may be subscripted)
B	Bandwidth required by a single stream (Mbps)
L	Sustainable bandwidth of a single disk (Mbps)
p_i	Probability of access of movie i
d	Number of disks required
P_C	Cost of a single disk of capacity C ($)
P_{FES}	Cost of a Front-End Server ($)
P_{VS}	Cost of a core Video Server ($)
P_1	Cost per stream of video ($)
f_{FES}	Fraction of requests served by the FES
G	Set of available disk sizes for use in a server implementation

As discussed in Chapter 2, several authors have noted that the storage cost of a video server is directly related to both the cost of providing storage and the cost of providing the bandwidth required by the streams [Tetz94] [Nuss95]. Accounting for only storage or bandwidth requirements will yield highly inaccurate cost estimates for a video server. As such a basic cost function for a video server is:

$$\text{Cost of VS} = f(N, K) \qquad \text{(Eqn 3.1)}$$

where N is the number of movies to be stored and K is the number of simultaneous streams supported.

As mentioned in Chapter 2 the actual configuration of storage in a video server is still a subject of active research. Storage hierarchies consisting of RAM, disk and tape in various configurations have been proposed, but never shown to be economically viable or able to provide sufficient quality of service. Magnetic disk is the one common device which appears in all proposals for interactive video servers. As such, disk technology forms the focus of consideration in this thesis. It is assumed (and shown to be viable) that disks and disk arrays will be used to store the entire movie library and to serve all customer requests. We now proceed to develop a cost model for a video server which uses disk technology to store and serve movies.

As already seen, the storage subsystem must satisfy the two requirements of sufficient capacity to store all movies and bandwidth to serve all customers. These two requirements can be expressed separately as follows.

The number of disks d_S required to satisfy the capacity requirement for all movies is:

$$d_S = \left\lceil \frac{KS}{C} \right\rceil \qquad \text{(Eqn 3.2)}$$

The number of disks d_B, required to satisfy the bandwidth requirement is:

$$d_B = \left\lceil \frac{NB}{L} \max(1, \frac{S}{C}) \right\rceil \qquad \text{(Eqn 3.3)}$$

The "max" term in Equation 3.3 is required for the situation where disk size is smaller than the requirements for a single movie (ie. S > C). In this case, we will require S/C times the number of disks given by the bandwidth constraint. The allocation strategy discussed here, however, actually relies on S < C for all C. In other words, at least one movie will always physically fit on a disk. This assumption is reasonable even if physical disks are smaller than that, since they

will be aggregated into striping groups large enough to provide storage for the entire film.

In general, to satisfy the total capacity and bandwidth constraints we must satisfy the strictest constraint for each individual movie to be stored. The above constraints must be combined in such a way as to account for the probability of access of each movie. More popular (hot) movies will have higher bandwidth demands which will dictate the number of disks required, while a less popular (cold) movie's disk requirement will be determined solely by the capacity required. In order to determine the total disk requirement a summation of the maximum of the two constraints over all movies is used.

$$d = \left\lceil \sum_{i=1}^{K} \left\{ \max\left(\frac{NBp_i}{L}, \frac{S}{C} \right) \right\} \right\rceil \qquad \text{(Eqn 3.4)}$$

Equation 3.4 accounts for both requirements of each movie and determines whether the limiting factor is storage or bandwidth. It then sums the requirements for every movie, to determine the total disk requirement for all K movies.

The above model satisfies the requirements of each movie individually and sums these requirements to gain an overall system requirement. This approach is suggested by [Doga94b]. The implications of this approach on server design are that considerable wastage of resources can occur. We discuss this in Section 3.4 and provide one method of minimising this wastage. An alternative solution is presented in Chapter 5.

3.3.1 Magnetic Disk Cost Model

The final step required to complete the cost model of a video server is an accurate model of the cost of individual disks. Equation 3.4 is used to calculate the number of disks required, with a model of disk cost, this can be converted to a total cost for the dominant aspect of a video server: storage. Disk cost can be assumed to be a function of

both capacity[2] and bandwidth[3]. Unfortunately, disk bandwidth varies significantly depending on the workload placed on it and is generally poorly specified by manufacturers. Indeed, typically mean seek times are the figure of merit used to specify disk drive speed, and this tends to be misleading. Another difficulty in comparing disk bandwidths (or transfer rates) is that they are often constrained by the bandwidth of the interface or bus. SCSI buses for example are constrained to 10MB/s (20MB/s for SCSI-II). Further, as will be seen, there is no significant correlation between seek time and cost. As such this is omitted from the cost model developed here. Instead we assume that all disks can sustain a certain fixed bandwidth for the comparison presented here. The method of determining this value of bandwidth that can be maintained by a single disk is discussed in Chapter 4.

In order to develop a model for disk cost, a large amount of pricing information was collected from a range of manufacturers and suppliers [Disk]. These prices were obtained in mid 1995 and are obviously subject to very rapid change. However, it is likely that the general price structure will remain similar, despite specific prices for individual drives falling dramatically over time. All prices used are retail and in $US. A total of 203 prices from 7 different suppliers were obtained. These prices covered a total of 70 different disk drives from 14 different manufacturers. The drives range in size from 1GB to 9.1GB. For each disk drive model, the mean was taken of the prices from each supplier and this mean plotted against disk capacity. A least squares method was then used to fit a linear approximation to the data. The results are shown in Figure 3.2.

2. The term "capacity" (or sometimes "size") in this thesis refers to the amount of data that can be stored on a disk or disk array. The fundamental units are measured in bytes.

3. The "bandwidth" of a disk (or disk array) is defined as the sustainable data rate of that device, and has units of bits per second.

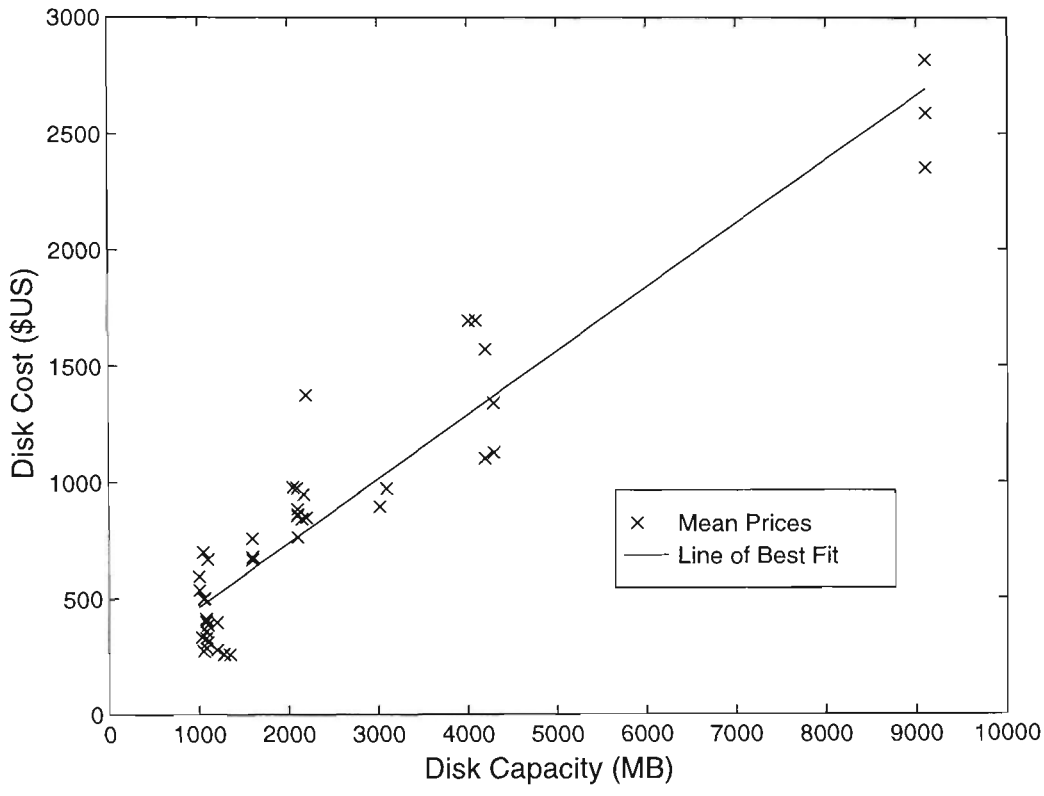


Figure 3.2 Disk cost vs capacity

The line of best fit shown in the figure has an equation of

$$P = 0.275C + 188 \qquad \text{(Eqn 3.5)}$$

where C is the disk capacity (in MB) and P is the cost in $US. From the data available it is clear from the graph that a linear approximation gives an accurate model of disk cost, particularly considering the high variance of the prices in the sample. The correlation between disk cost and capacity has been calculated to be 0.944. Recalling that perfect correlation results in a figure of 1.0 with totally uncorrelated data returning 0, this reinforces the very strong correlation shown in the figure.

In order to determine the effect of bandwidth on disk cost, the prices obtained were further separated according to the seek time specified by the manufacturer. Before comparing prices with seek times however, prices for all drives were normalised with respect to their capacity using the linear with offset model shown in Equation 3.5. The prices (normalised to the price of an equivalent 1GB drive) for all

drives in the sample are shown plotted against seek time in Figure 3.3. As can be observed from the least-squares line of best fit, there is no apparent correlation between disk seek time and cost. Indeed the large spread of cost figures at each different seek time indicate that pricing is more closely related to other factors (eg. market forces) than the questionable figure of merit of seek time.

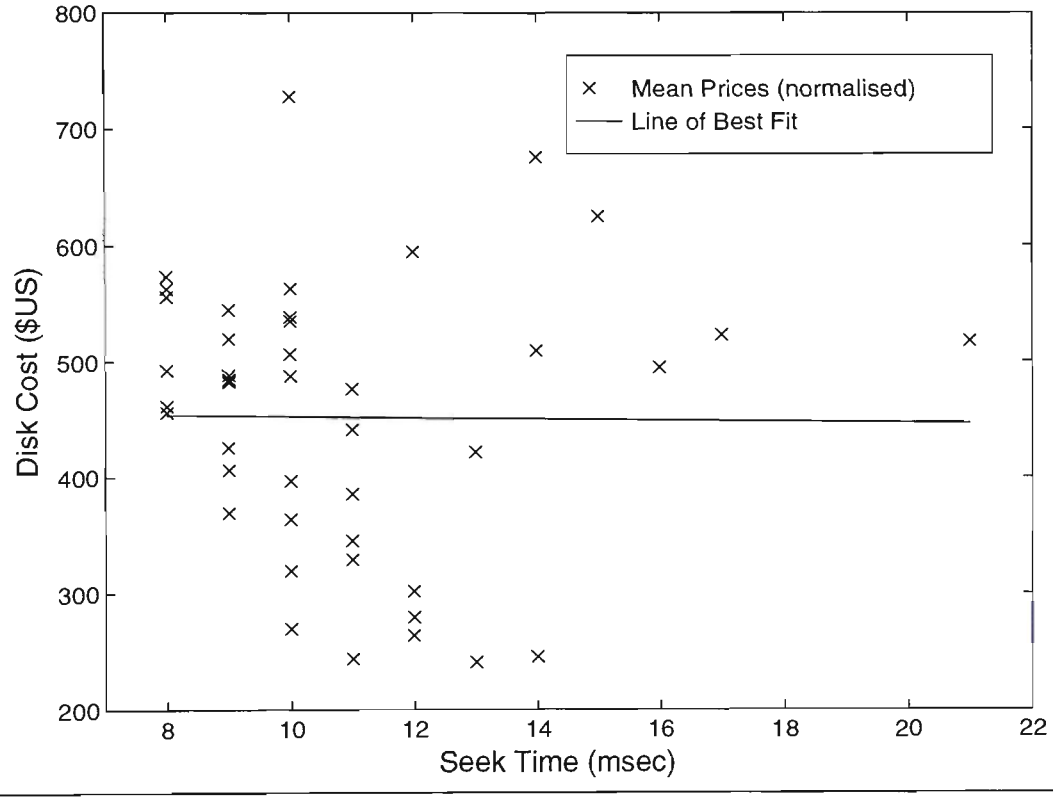


Figure 3.3 Disk cost vs seek time

The statistical correlation between seek time and disk cost has also been calculated and is -0.0126. This is reflected by the shallow negative gradient of the line shown in Figure 3.3 and implies that there is a very small (negligible) negative correlation between seek time and cost.

Since there is no readily available correlation between cost and throughput (poorly modelled by seek time) of magnetic disk drives, we are forced to assume a given throughput for a disk drive and use the cost model based purely on capacity as shown in Equation 3.5.

The assumptions made concerning throughput will be stated and justified where it is first used in Section 3.4.2.

Having developed a cost model for magnetic disks, the next section combines this with the drive requirement of a server shown in Equation 3.4 to determine realistic costs for two server design methods.

3.4 Homogeneous vs Heterogeneous Disk Arrays

This section develops a complete model of the cost of storage of a video server. Initially a homogeneous disk architecture is assumed. By homogeneous it is meant that all disks in the system have the same capacity and bandwidth. Under reasonable assumptions it is revealed that such an approach can be very wasteful of both bandwidth and capacity resources within the server. For this reason we have earlier proposed (see [Barn95a] [Barn96c]) an heterogeneous approach to storage whereby disk capacity (and as such cost) is varied according to the popularity of the movie being stored. Before investigating storage costs however, an accurate model of video popularity is required.

3.4.1 Video Popularity Model

One of the major influences on the requirements for a given movie is the probability of access. As discussed in Section 2.2.2 video popularity has been modelled in a number of different ways by various authors. The most commonly considered application is Video-On-Demand, since demand patterns are likely to be similar to existing video rental markets for which data (albeit limited) is available. In [Cher94] it is asserted that the data from a single week of rentals of the Top 50 videos can be well matched by a Zipf distribution (excepting the top 4 movies which are considerably more popular than suggested by Zipf's Law). Zipf's law can be stated as:

$$p_i = \frac{C}{i} \qquad \text{where} \qquad C = \frac{1}{\sum_{i=1}^{K} \frac{1}{i}} \qquad \text{(Eqn 3.6)}$$

where p_i is the probability of access of the i'th movie, and the movies are arranged in decreasing order of popularity. Notice that C is a constant based on the number of movies under consideration. As such the terms of p_i form a harmonic series the sum of which is divergent, which leads to the dependency of C on the number of movies. The importance of this arises because it implies that a good fit for a particular movie population (eg. 50 titles) will not translate to a good fit for larger populations. Several authors (eg. [Nuss95]) employ a Zipf model based on the observations of [Cher94] but with a much larger number of movies (ie. increased K). This change in K affects the normalising constant C of the Zipf distribution which in turn alters the individual probabilities of access for all movies. Of course a change in the value of C is necessary in order to ensure that access probabilities all sum to 1, but it is now not clear that the Zipf model is accurate for the larger numbers of movies.

In a series of papers from IBM Research ([Dan94a], [Dan94b], [Dan94c], [Dan94d], [Dan94e], [Dan95a]) the authors model object popularity with a parameterised Zipf distribution represented by:

$$p_i = \frac{C}{i^{(1-\theta)}} \qquad \text{where} \qquad C = \frac{1}{\sum_{i=1}^{K} \frac{1}{i^{(1-\theta)}}} \qquad \text{(Eqn 3.7)}$$

where θ is given a value of 0.271. The authors demonstrate (based on limited statistical data) that this provides a good fit for popularities of the top 100 movies.

As already mentioned accurate statistical data portraying movie rental popularity is difficult to obtain. This is reflected by the fact that Chervenak relies on a single week of data to draw the conclusion regarding the disk model. Two publications with some credible data are [Bure94] and [Fist94]. Figure 3.4 shows the two Zipf distri-

butions discussed above along with the empirical data points from these papers.

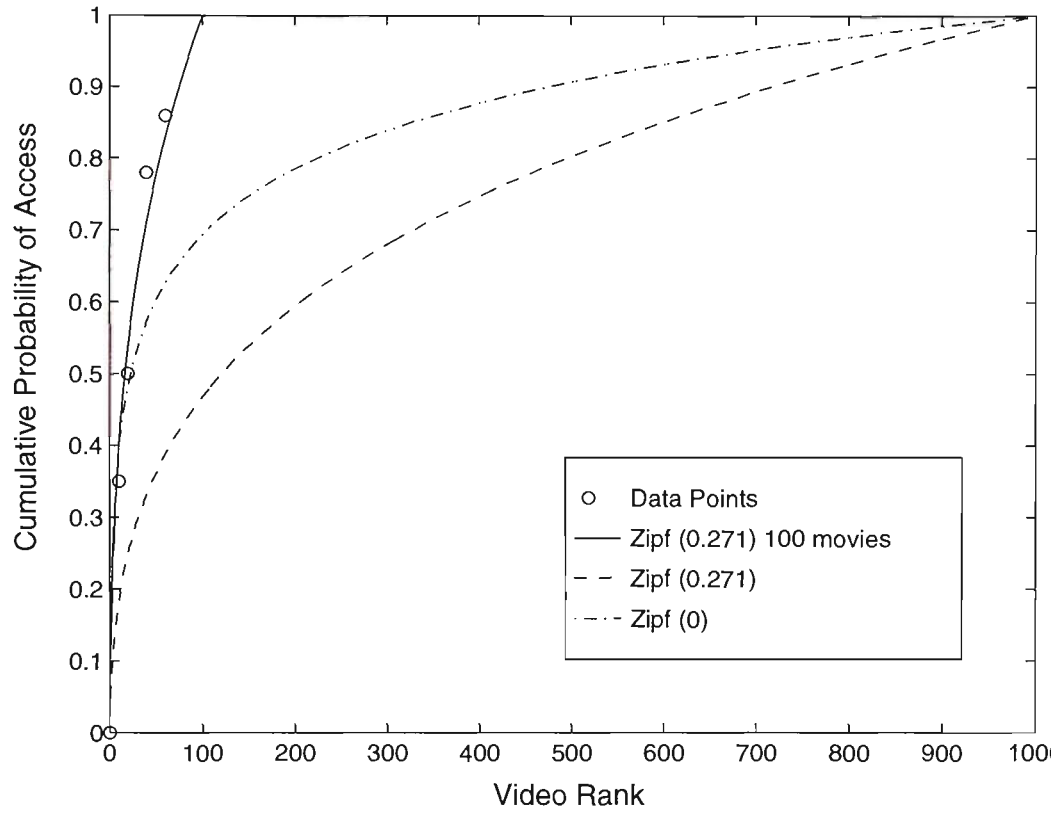


Figure 3.4 Cumulative distribution of video popularity for various models (assuming a total of 1000 movies)

The solid line in Figure 3.4 represents the Zipf distribution with a parameter of 0.271 for a total of 100 movies as used by Dan et al. In this case the model matches closely with observed data. When the Zipf model is used for larger movie populations (1000 in the figure) it is clear that the access probabilities of the model depart significantly from the empirical data. Numerous papers actually utilise Zipfs law for databases up to 10,000 titles resulting in a severe underestimate of the popularity of the top ranked titles.

To avoid the deficiencies of the Zipf distribution used above, an empirical approach to video popularity has been used in this thesis. A simple curve fitting approach is used to yield a good fit to empirical data for a larger movie population. The function obtained is used in simulation studies to map uniform random variables to a suitable

random variable representing the popularity of a video in a given rank.

For the case of a population of 1000 movies in total, the transforming equation has the following form:

$$y = -9.11 + 1.63\exp(2.19x + 1.72) + 0.027\exp(12.3x^{3.28} - 1.873) \quad \text{(Eqn 3.8)}$$

Here x is a U(0,1) random variable and the function returns y, the rank of the video being accessed. This transformation is used in simulation studies presented later in the thesis.

Although complex, this equation provides a very good fit to the data points as shown in Figure 3.5. It must be noted that for other video

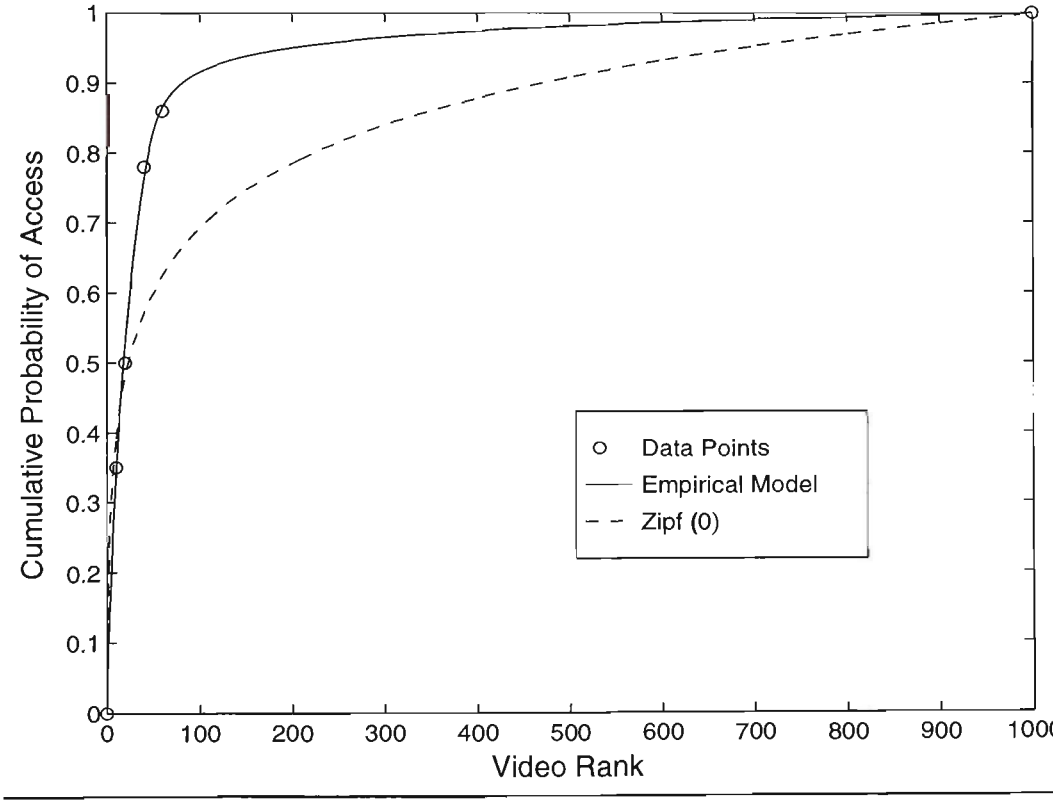


Figure 3.5 Empirical model of video popularity for a total movie population of 1000

populations different empirical models are required to provide a good fit to the data points. Also, due to the uncertainty of the relationship between current video rental statistics and future interactive video demand statistics, this thesis considers results for both

the empirical distribution and the Zipf models commonly used elsewhere in the literature. The next section combines the work presented thus far to determine the total cost for a server based on homogeneous disk arrays.

3.4.2 Homogeneous Storage Costs

Assuming that the requirements of each movie must be satisfied by a given group of disks leads to the cost model already shown in Equation 3.4. In an homogeneous system, it is assumed that all disks have the same capacity and bandwidth. As such the popular movies will probably require several disks in order to satisfy bandwidth requirements, while long unpopular movies will require only one disk for that reason but may require several disks to meet capacity constraints. Hence there is a problem in selecting the optimal disk capacity, for a given bandwidth in order to minimise the total storage cost.

Ideally, selecting the appropriate capacity for each disk drive would result in 100% utilisation of both bandwidth and capacity resources. This could be achieved by matching the ratio of capacity and bandwidth of the disks to that of the customer population [Tetz94]. For the architecture described above, however, the actual optimal disk size depends on shape of the popularity distribution of the movies. An example is shown in Figure 3.6. Cost of storage versus disk size is shown for both the empirical model of Figure 3.5 and an unrealistic uniform model where all titles are equiprobably accessed. The other parameters used in this study are listed in Table 3.2.

The graph in Figure 3.6 reveals that a disk size of 5 GB is optimal when the popularity of movies is uniform. This size is easily explained as it balances the ratio of disk bandwidth to capacity (30Mbps / 5GB) to the ratio of customers (bandwidth) to movies (capacity) in the population (4000 * 3Mbps / 1000 * 2GB). When the empirical model is used, however, 2GB is optimal disk capacity, but

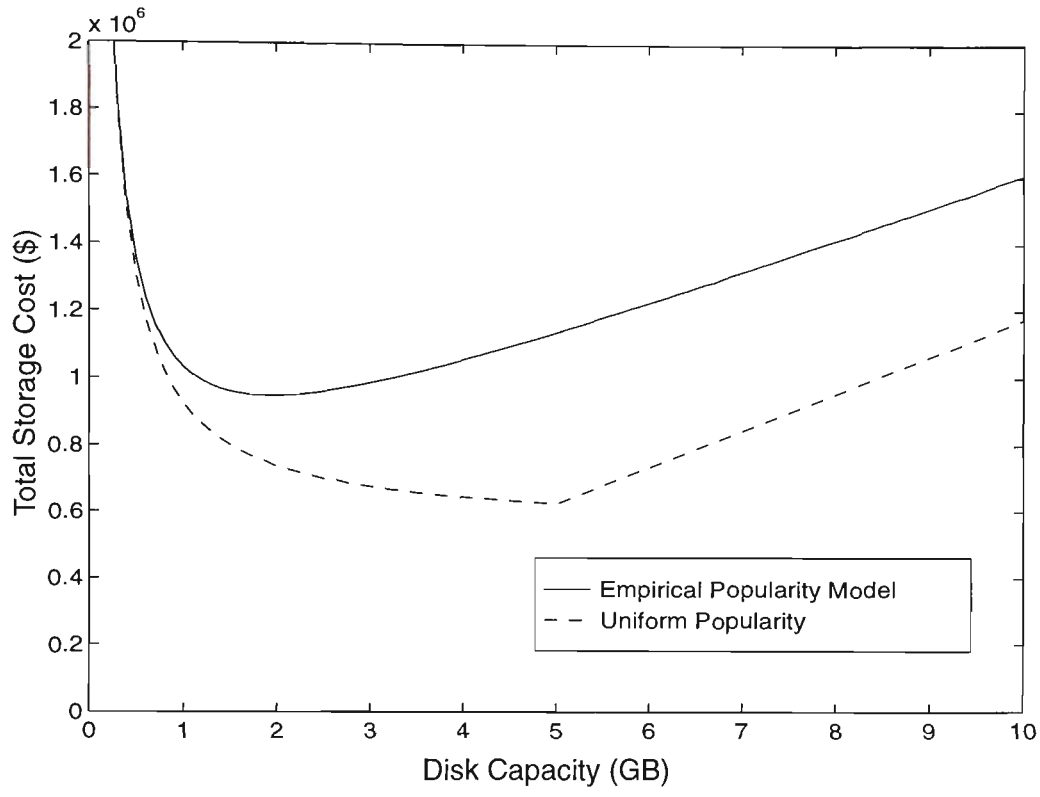


Figure 3.6 Total storage cost vs selected disk capacity for the parameters shown in Table 3.2

Table 3.2 Parameters used for Figure 3.6

Parameter	Description	Value
N	Number of customers (peak)	4000
B	Bandwidth requirement per stream	3 Mbps
L	Sustainable bandwidth of a single disk	30 Mbps
S	Storage required by a single movie object	2 GB
C	Capacity of a single disk	Varies
p_i	Popularity of movie i	Empirical or Uniform

results in a significantly higher cost than the uniform case. The reason for the increased cost when the popularity is skewed becomes clear from an examination of the bandwidth and capacity utilisations in each case. Figure 3.7 shows both capacity and bandwidth utilisations for the empirical and uniform popularity cases (see Table 3.2 for parameters[4]).

4. The value used for L, disk drive bandwidth, is taken from the lower end of claims by manufacturers including Maxtor and Micropolis. [Max95] [Mic94] and is supported by figures in [Brub96] and [Chan96b]. Chapter 4 develops a model for determining realistic sustainable throughput from physical disk drive parameters.

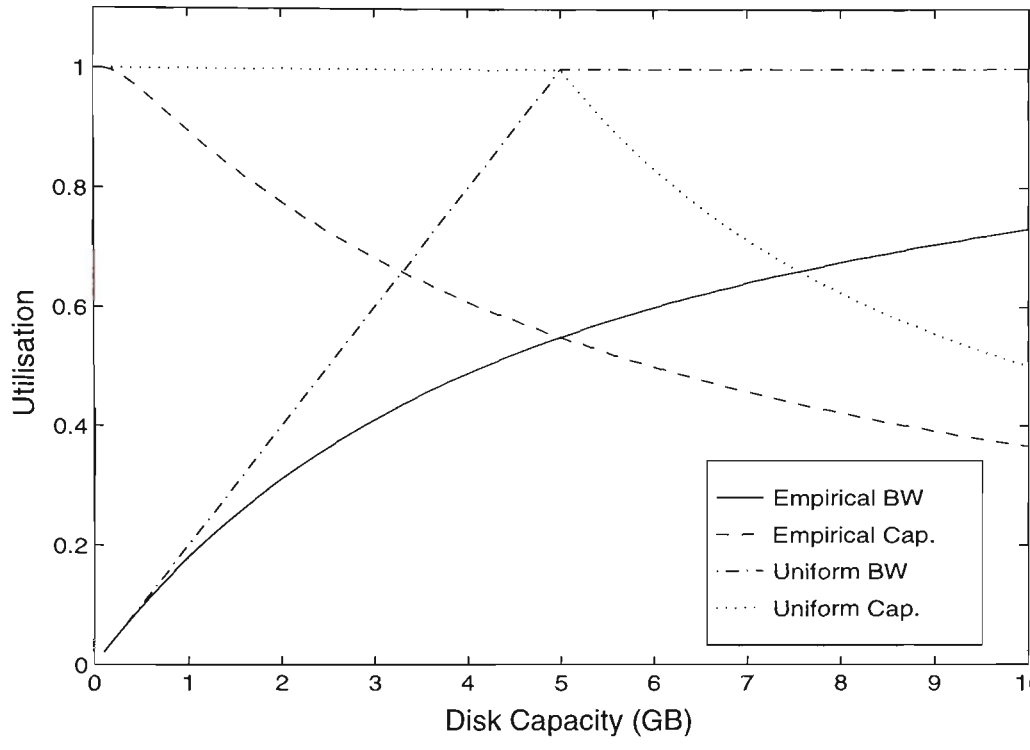


Figure 3.7 Bandwidth and capacity utilisations for both empirical and uniformly distributed popularities

For the uniform probability case, both capacity and bandwidth resources are fully utilised at a capacity of 5GB and hence this results in the minimum cost. For the empirical case, however, even at the minimum cost point (2GB capacity) neither bandwidth nor capacity is fully utilised. Indeed there is no point where both resources are fully utilised, and finding the optimal operating point is clearly closely related to the assumed distribution of movie popularity. The next section elucidates on the causes of this problem and proposes an architecture capable of alleviating it.

3.4.2.1 Inefficiencies of Homogeneous Approach

Even when using the most efficient disk size for a particular circumstance, considerable wastage still occurs in the homogeneous system when a skewed popularity distribution is assumed. Figure 3.8 shows the capacity and bandwidth utilisations of the top 200 movies for the empirical distribution for the optimum disk size (in terms of overall cost) of 2GB.

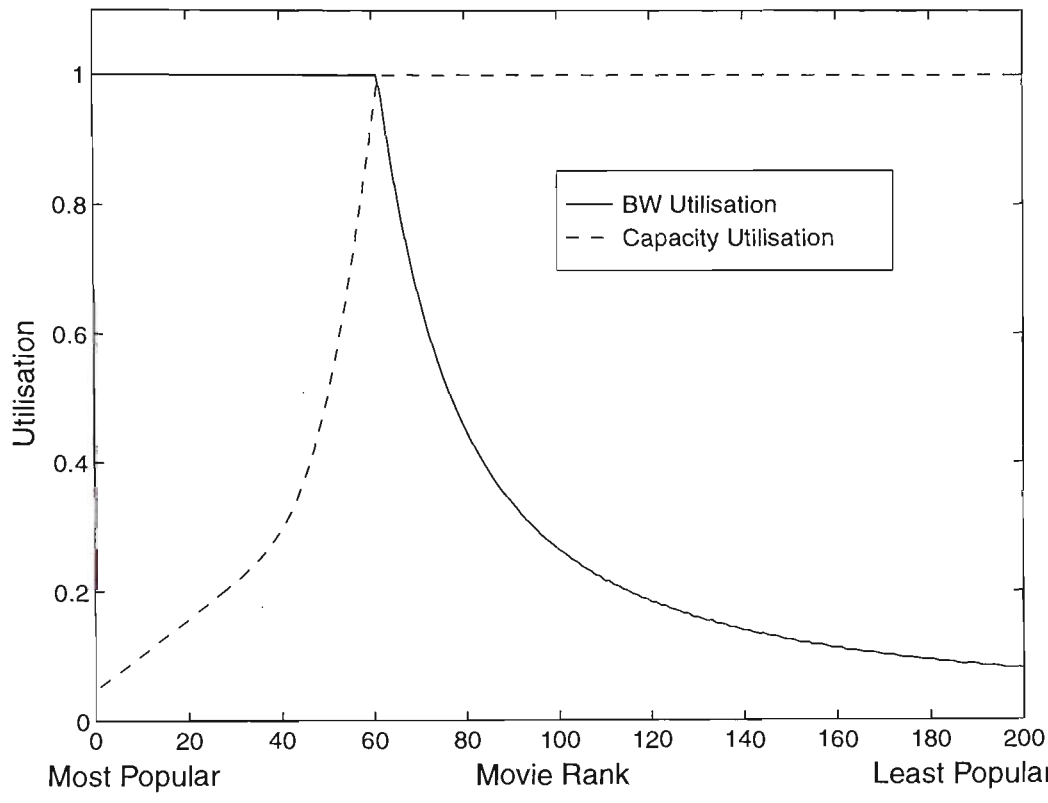


Figure 3.8 Bandwidth and capacity utilisation versus movie rank for a disk capacity of 2GB for the empirical popularity case

It is clear that popular movies are wasting capacity resources (ie. they are bandwidth limited), while unpopular movies squander bandwidth resources (they are capacity limited). Indeed, only one movie gains almost perfect utilisation of both capacity and bandwidth (the movie ranked 62 in this case). Figure 3.9 represents these inefficiencies graphically, comparing the use of small disks and large disks for a given system.

As can be seen from Figure 3.9 popular movies make efficient use of both capacity and bandwidth resources when stored on suitably small disks. Alternatively unpopular movies (when assumed to be of a similar length) are most efficiently stored by combining several of them together onto a large disk (or a group of large disks). Note that the diagrammatic approach does not accurately portray the number of disks or the physical layout in either case, but is merely intended to illustrate the idea that popularity of a movie effects the disk capacity that can be most efficiently used to store and serve it.

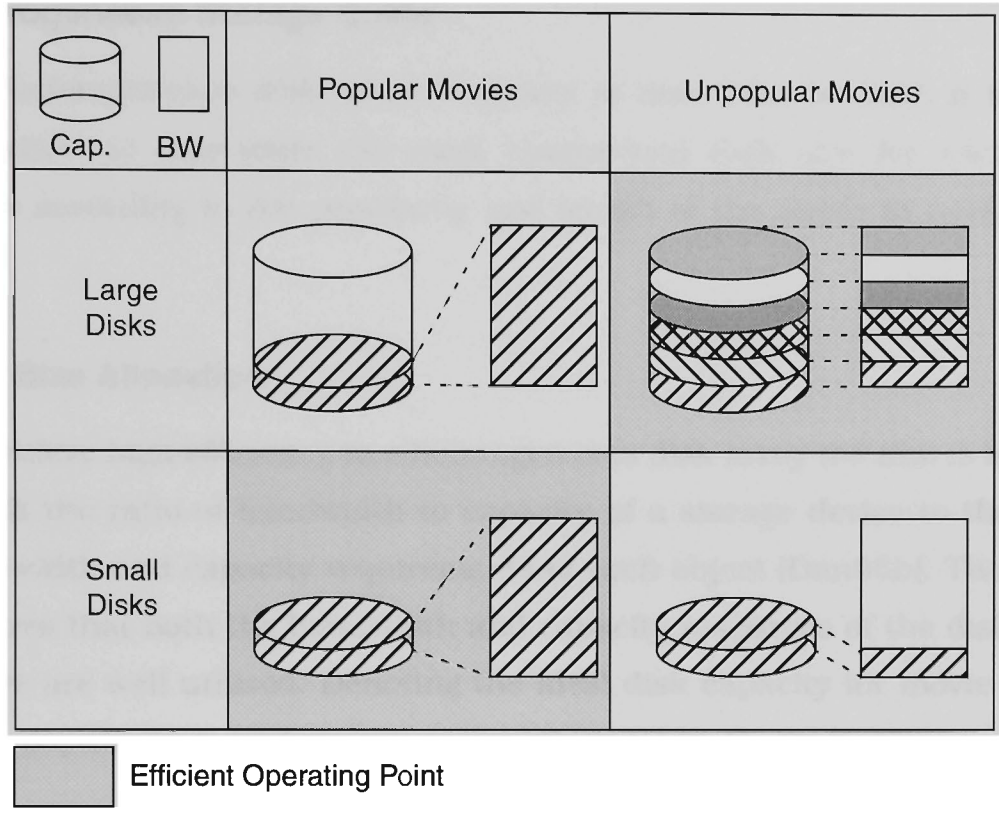


Figure 3.9 Efficient operating points for various disk sizes

The realisation that different movies can be efficiently stored on different media is of course not new. This is precisely the idea that prompts the proposition of storage hierarchies consisting of RAM, disk and tape technologies as discussed in detail in Chapter 2. However, due to problems of cost and long latencies, RAM and tape systems have been difficult to justify. These facts combined have lead us to the idea of a heterogeneous disk system whereby movies are placed on different capacity disk drives (effectively altering the capacity-bandwidth ratio) depending on their popularity. Such a system maintains the intuitive appeal of the more general storage hierarchy without incurring the penalties of the other storage media.

It should be noted that the heterogeneous approach is not the only method of overcoming the inefficiencies depicted in Figure 3.9. Chapter 5 considers another efficient scheme in some detail. The following section develops the idea of a heterogeneous disk based storage architecture.

3.4.3 Heterogeneous Storage Costs

In a heterogeneous disk array, a variety of disk sizes is used. It is important to determine the most appropriate disk size for each movie according to the popularity and length of the movie in question.

3.4.3.1 Disk Size Allocation

To achieve high efficiency in a heterogeneous disk array the aim is to match the ratio of bandwidth to capacity of a storage device to the bandwidth and capacity requirements of each object [Dan95b]. This ensures that both the bandwidth and capacity resources of the disk arrays are well utilised. Denoting the ideal disk capacity for movie i (with popularity p_i and storage requirement S_i) by C_i, we have:

$$\frac{C_i}{L} = \frac{S_i}{NBp_i} \qquad \text{(Eqn 3.9)}$$

Since C_i is the dependent variable, rearrange Equation 3.9 to obtain:

$$C_i = \frac{S_i L}{NBp_i} \qquad \text{(Eqn 3.10)}$$

By using the overall bandwidth (or storage) requirement of the movie, it is then possible to calculate the total number of disks of size C_i required for movie i.

$$d_i = \frac{NBp_i}{L} \qquad \text{(Eqn 3.11)}$$

Having determined the number of disks required for each movie the cost can be calculated from Equation 3.5. This highly idealised model of an heterogeneous disk array returns the same minimum cost for the parameters shown in Table 3.2 under the empirical distribution of popularity as the homogeneous system did for uniform popularity (see Figure 3.6). More simply, by selecting precisely the correct disk size for each object, and allowing fractional numbers of these disks to be used, the ideal heterogeneous system has over-

come the inefficiencies caused by varying movie popularities which resulted in increased storage costs in the homogeneous system.

In order to be realistic, however, further constraints must be placed on the heterogeneous model used above. Specifically, Equation 3.10 implies that any disk size is available, whereas in reality only a small number of discrete disk sizes are manufactured. Also, Equation 3.11 implies that a fractional number of disks can be included in the system. However, disk numbers (of each size) must, in reality, be restricted to an integral value. By incorporating these two constraints we obtain a much more realistic model of an heterogeneous disk based storage architecture. Note, however, that Equation 3.10 and Equation 3.11 do provide a lower bound for storage costs.

The approach to meeting the above two constraints is to specify a set of allowable disk sizes, G, and then select the size for a particular movie that most closely matches the size given by Equation 3.10. Figure 3.10 shows an example where available disk sizes are limited to 0.5, 2, 5, 8 and 10 gigabytes, ie.

$$G = \{0.5, 2, 5, 8, 10\}. \qquad \text{(Eqn 3.12)}$$

Once the appropriate disks sizes are selected, the total requirement of each size is easily obtained through summation (and applying a ceiling function) and the total system cost immediately follows. Figure 3.11 shows an example of total system cost for the parameters in Table 3.2 for a variety of different disk allocation methods. The method applied in each case of the figure is described in Table 3.3.

Table 3.3 Description of the various cases compared in Figure 3.11

Case	Description
1	Homogeneous Storage Cost G = {2}
2	Heterogeneous Storage Cost G = {1, 10}
3	Heterogeneous Storage Cost G = {0.4, 1, 2, 4, 10}
4	Heterogeneous Storage Cost G = {0.2, 0.5, 1, 2, 4, 6, 8, 10}
5	Idealised Heterogeneous Storage Cost G $\in \Re$

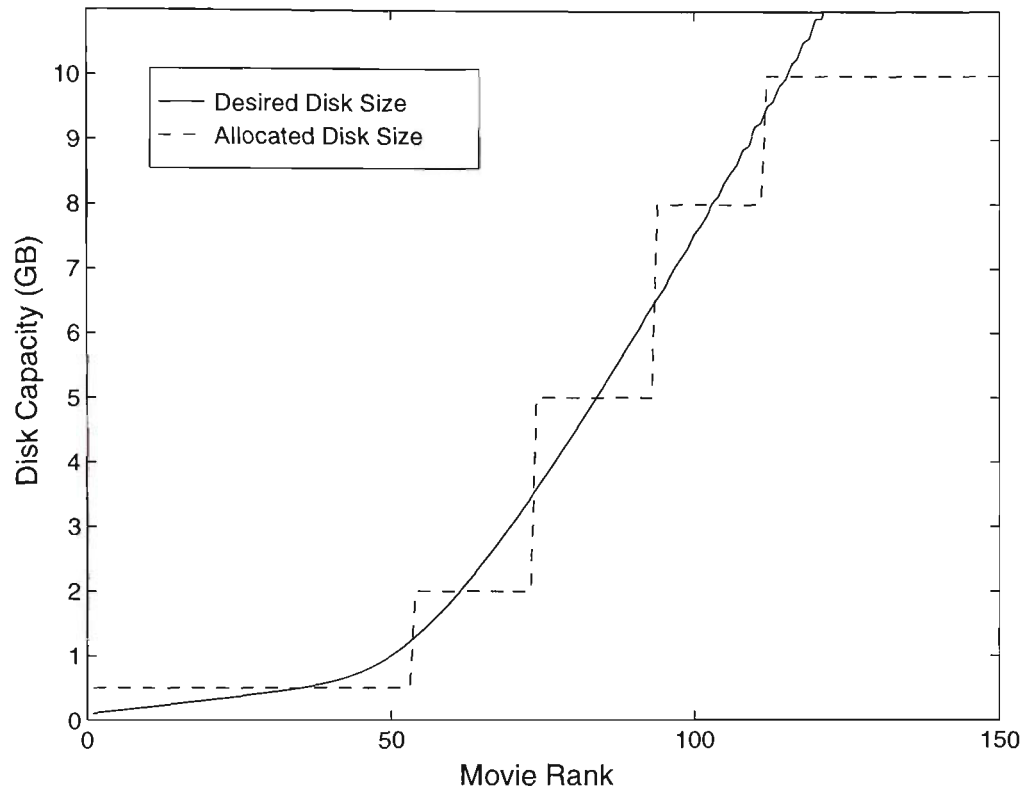


Figure 3.10 Selection of discrete disk sizes for individual movie objects.

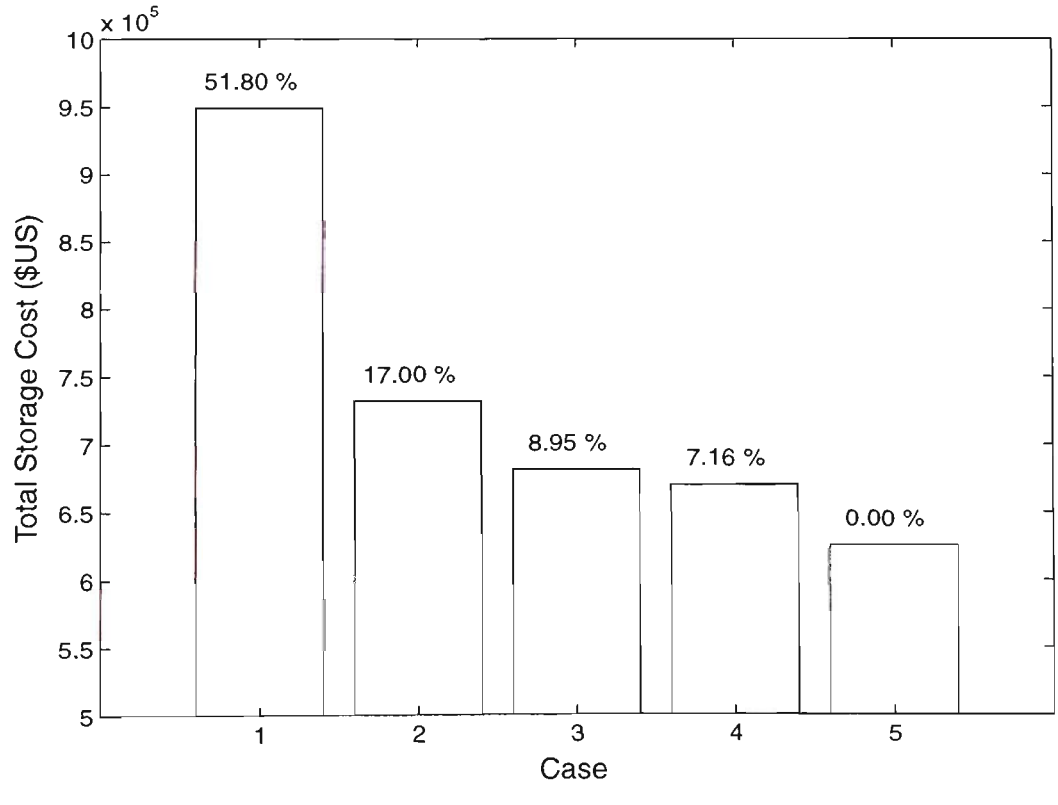


Figure 3.11 Comparison of homogeneous and heterogeneous schemes with the lower bound of storage cost.

Figure 3.11 reveals that an appropriately designed realistic heterogeneous storage system can closely approximate the same ideal cost given by the idealised heterogeneous system. Note that the disk sizes used in this example are not selected to be optimal, instead it is assumed that particular disk sizes are available in a given case, and the heterogeneous design procedure attempts to use these optimally. Selecting the most useful disk sizes for a given system is an exercise in fitting a piecewise linear model to the popularity curve of the entire video population. Each straight line corresponds to the bandwidth to capacity ratio of a single disk drive. Notice that even though the disk capacities selected for use here are not optimal, the five disk heterogeneous system proposed in case 3 is less than 10% more expensive than the absolute optimal system obtained using the highly idealised heterogeneous system of Equation 3.11.

It is possible to further optimise this heterogeneous system by searching for cases where a movie could be stored on a smaller disk without causing any increase in the number of smaller disks required. This optimisation provides only slight improvements and is discussed in Appendix A.

Before proceeding, it is important to reiterate that the above storage methodology has not been optimised particularly thoroughly. Indeed, this is not the purpose of this chapter. Instead the goal was to develop a realistic (as opposed to optimal) model of video server storage cost based on a physically realisable architecture. This is intended to be used in place of previously proposed cost models which are based purely on suppositions of how storage costs might scale with server size. The model that has been derived is straightforward and can be seen to give credible results for a reasonable set of assumptions. In the following section this model is utilised to perform a comparison of various network architectures for interactive video services. The issue of optimising the storage system within a video server is revisited in Chapter 5, where suitable packing heuris-

tics are applied to homogeneous disk arrays in order to overcome the drawbacks of heterogeneous systems.

3.5 Distributed vs Centralised Approaches to Storage

The earlier sections have developed a realistic cost model for magnetic disk based storage servers. The model that has been developed accounts for both variable movie popularity and realistic models of disk drive performance and price characteristics. Using this model we are now in a position to provide a useful comparison of centralised and distributed approaches to storage in interactive video systems.

The essential difference between centralised and distributed approaches is related to where storage is located within the network. As indicated in Figure 3.1 this effects the bandwidth being transmitted across the core network. Clearly the more the storage is distributed toward the customer, the lower the bandwidth costs. The actual reduction seen will depend entirely on network topology and, although easily calculated for a particular topology [Nuss95], is not considered here. The relationship between storage distribution and cost, however, is not so clear. Indeed it would appear that storage costs would increase as duplication of objects is increased in the distributed approach. This could possibly negate and override the bandwidth savings.

The extremely skewed popularity distribution of interactive video systems ensures that caches at the FES can serve a large proportion of the customer population by only storing a small number of movies. For example, a cache of just 21 movies is likely to be able to satisfy 50% of customer requests [Fist94]. In order to compare centralised and distributed storage costs we assume a certain total customer population and then use either a large single central server to serve all customers, or several small front-end caches combined

with a low throughput central server which handles only the requests not served by the front end caches. Table 3.4 shows the percentage of requests served by a front end server related to the number of movies stored there. This table follows directly from the popularity distribution developed in Section 3.4.1.

Table 3.4 Movies stored and requests served by a Front-End Server

% Requests Served by FES (f_{FES}*100)	80	85	90	95	99
Number of Movies Required	45	55	82	200	680

Using this table, distributed and centralised approaches are compared using a methodology designed to match realistic public networks. It is assumed that each FES will serve approximately the same number of homes and that this number is in the order of 10,000 per FES. This is in keeping with the number of homes currently connected to a local exchange in existing telephone networks. If we assume a busy-hour average load of 40% (which closely matches peak load currently experienced in broadcast television systems, see Figure 4.7) this requires each FES to support an average load of 4,000 streams during the busy hour for true interactive video to each home. Further it is assumed that a total of 1,000 different movie titles must be available to all customers. The number of video servers located in the core of the network will depend on the size of the cache at the FES, but it is assumed that each VS is capable of handling a maximum of 4,000 streams also, and that the VS must store all 1,000 movies. Using this methodology the cost per stream of providing interactive video services to a large user population can be calculated using the cost function derived in Section 3.4.3. Figure 3.12 shows the cost per stream versus the percentage of streams served by the FES cache under the above assumptions, using the heterogeneous storage system. The cost per stream is calculated from the cost of each FES and the VS from Equation 3.13.

$$P_1 = \frac{P_{VS}(1 - f_{FES}) + P_{FES}}{N} \qquad \text{(Eqn 3.13)}$$

where the prices of the individual servers (see Table 3.1) are obtained using Equation 3.5, Equation 3.10 and Equation 3.11, with the available disk sizes (the set G) suitably constrained as follows.

For the results shown in Figure 3.12, five disk sizes have been used for both the FES and VS design, and the disk sizes chosen to ensure a high efficiency. For example, the caches are only serving a small number of popular movies and as such a range of small disks is most suitable ($G = \{0.2, 0.5, 1, 2.5, 4\}$). The VS in the core network, however is serving movies with wide ranging popularities and as such a wide range of disks sizes is applicable ($G = \{0.4, 1, 4, 8, 10\}$).

As a result of these disk size selections, all of the server designs in the results of Figure 3.12 achieved an aggregate efficiency in excess of 85%. This implies that no more than 15% of bandwidth or capacity resources of the disks were wasted by any system.

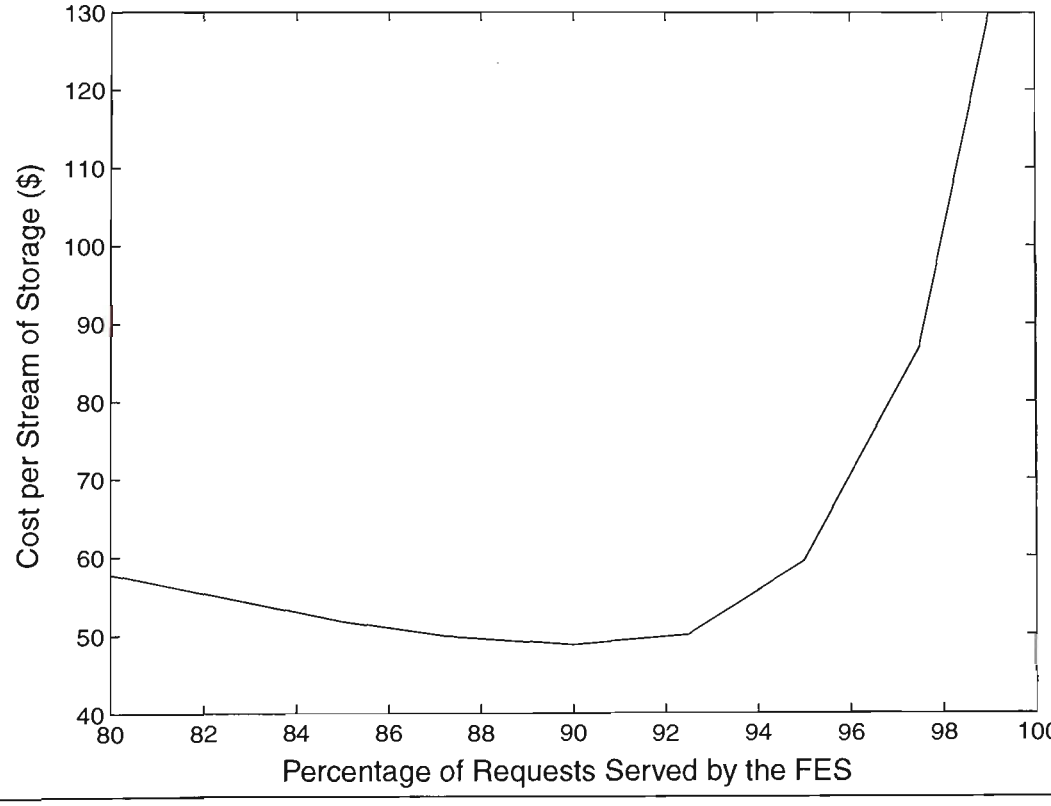


Figure 3.12 Distributed storage cost versus percentage of requests served by FES

Figure 3.12 reveals that minimum cost is attained when approximately 82 movies are cached, resulting in each FES serving approximately 90% of requests. It is interesting to note that the "knee" of the movie popularity distribution shown in Figure 3.5 occurs at about this point. Caching any more movies than this causes storage costs to rise more rapidly for a decreasing benefit.

An important comparison is between the distributed and centralised storage costs. It has been shown above that distributed storage costs are minimised when about 90% of streams are served at the FES and that this results in a capital cost per stream of about $49 for the situation described here. Next consider the case of a single centralised server capable of serving a much larger number of streams, say 20,000. Such a server constructed in a heterogeneous fashion with 5 disk sizes, also running at greater than 85% efficiency incurs a storage cost in excess of $53 per stream (using the same methodology as above). More simply, for this particular case, the cost per stream in the centralised case is higher than the distributed case, purely in terms of storage. This is a result of the fact that disk storage is inherently better suited to the bandwidth to capacity ratios found in the distributed approach. As already discussed, it is obvious that regardless of network topology the centralised architecture will also cost considerably more than the distributed case in terms of bandwidth and infrastructure costs. For example, serving 20,000 streams requires 60Gbps of network bandwidth from a single point to a diverse area.

It should be noted that the conclusions drawn here result only from assumptions made regarding server architecture and that these assumptions may not hold depending upon the actual server design used in a particular instance. The results shown here, however, do agree well with those shown in the literature [Nuss95] [Tetz94] in that caching of popular titles close to customer populations is economically sensible.

The value of the method used here is that no assumptions were required regarding the network architecture, since it was not necessary to account for bandwidth costs in the analysis. Considering bandwidth costs would, however, certainly serve to reinforce the conclusions presented here. Bandwidth costs have been avoided here due to their heavy dependence on core network topology and on the weighting between storage and bandwidth costs which is difficult to quantify in a general fashion. Depending on the assumptions made for bandwidth costs (Nussbaumer et al. [Nuss95] assume that they are similar to storage costs) the argument in favour of distributed storage is considerably enhanced. This is easily accounted for by the arguments associated with Figure 3.1.

One implicit assumption in the above result is that the FES cache will always store the most popular set of movies at any time. This is necessary if the cache is to be able to serve the number of requests suggested by the popularity distribution. In order, to confirm that the cache will be able to maintain consistency given changing video popularities, caching algorithms are investigated in the next section. It should be noted that this issue has been totally ignored by the literature, with all previous work preferring to assume that a cache will always be able to store the current Top M movies.

3.6 Caching Algorithms for the Front End Server

Given that a distributed architecture is most cost effective in terms of both storage and bandwidth, it is important to consider how to maintain the efficiency of the distributed approach. The figures of Table 3.4 only apply if the cache is storing the most popular movies at all times. If the cache is storing unpopular titles, the percentage of customers served by it will be very small, with a consequent increase in load on the VS and on overall system cost. As such, it is critical to the efficiency of the system that the cache currency be maintained at all times. Although caching algorithms for computer systems are

well studied (see for example [Kare94]), the same algorithms are not really applicable here.

Standard computer caching algorithms must be simple enough to be implemented in hardware and operate extremely quickly to yield benefits over a reference to main memory. In the case of an interactive video cache located at the FES, the algorithms can be considerably more complex, since the timescales of operation are much longer. Also the same locality-of-access ideas that are seen in computer systems do not apply here. Indeed, as a first step in evaluating the efficiency of a FES cache a model of video popularity variation with time is required. Put simply, such a model would reflect how the popularity of a given movie title would change over its lifecycle from the date of release to a date when it is very rarely selected at all.

3.6.1 Video Popularity Variation Model

When a video is initially released it can be observed to move quickly to its highest ranking and then move slowly down (with occasional rises) through the chart over time before eventually dropping out of the chart altogether. An example of this trend is shown for the movie "River Wild" from the time it was originally released in Australian cinemas in November, 1994 in Figure 3.13 [MPDA95].

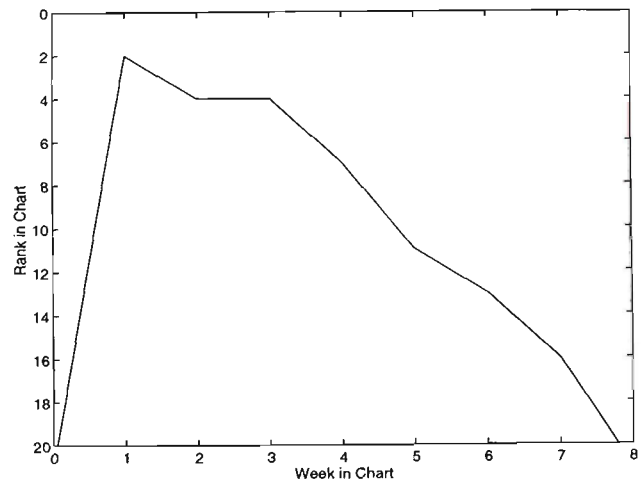


Figure 3.13 Life cycle of "River Wild" following Australian cinema release

The "lifecycle" of this title is representative of several titles investigated. There are of course exceptions, such as science fiction movies which although never reaching a high rank, seem to remain fairly constant for very long periods of time. Other "cult" movies may move very quickly to a high ranking before dropping out of the charts just as quickly. It is difficult to account for all of these variables in a model for chart movement and even more difficult to justify the complexity of such a model since validation is a large problem due to the low availability of truly relevant data. The modelling approach described below is a simple algorithmic approach aimed at accounting for the major artefacts observed in a brief investigation of movie popularity variation. It will be shown in Section 3.6.1.1 that this approach gives credible results.

The algorithm starts with videos filling each of the K (say 1000) available slots. At discrete intervals of time, each video will move a certain distance either up or down the chart. The distance that a video moves is a uniform random variable which is proportional to its current rank (with a constant of proportionality, α). That is, lower ranked videos move more quickly (either up or down) than higher ranked videos. This captures the fact that a video will climb very quickly until it reaches its peak, and also that a descending video will descend more quickly as it proceeds lower down the chart. A video that is moving up the chart will turn around and start moving down with some probability p. A video that is moving down, will continue to move down. When the rank of a video is greater than 1000, it has dropped off the bottom of the chart and is replaced by a new video, which is inserted into an available slot and initially set to move up the chart. It is important to note that the available slots are spread evenly throughout the chart and not concentrated at the bottom. This is because the algorithm commences moving videos from the top of the chart and works down, which often means that a high level slot won't be filled until we go through the process of filling the empty slots with "new releases". The algorithm used generates a

chart matrix with each column representing a week and each row a video rank.

Note that the algorithm described above relies on just two parameters, α and p. By altering these two parameters we can alter how long on average a title stays in the chart, and how quickly it rises and falls. Figure 3.14 shows the chart movement generated for some selected videos (represented by integer id's) by the above algorithm for values of $\alpha = 0.2$ and $p = 0.2$. It is observed (visually) that the chart trajectories of various titles tends to follow the trends observed for actual titles (see Figure 3.13).

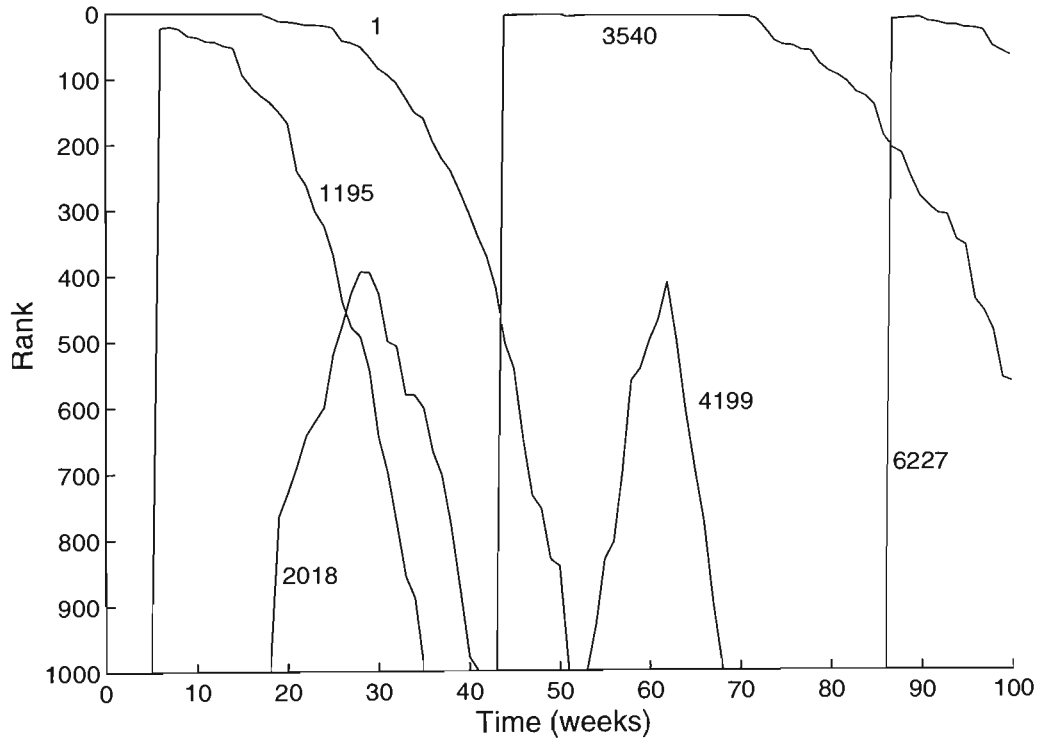


Figure 3.14 Example output from algorithmic popularity model of video lifecycle

3.6.1.1 Validation of the Algorithm

Although a model of popularity change with time is relatively easy to develop, the lack of empirical data on this topic makes detailed validation difficult. Although movie data was used in the example in Figure 3.13, such data is only available in small quantities and generally only represents the Top 10 or 20 titles in a chart. As such, an

alternative source of empirical data has been used in this thesis. Each week the Australian Records Industry Association (ARIA) releases detailed charts of the Top 50 music albums and singles sold during the past week. Due to the unavailability of similar information for video rental, it is these statistics that are used to validate the model of video popularity presented here.

In order to gauge the usefulness of our chart movement algorithm we compare several statistics of our charts to those of actual charts from the music industry. The statistics used to compare the two are:

- Highest ranking achieved
- Number of weeks in the Top 50
- Area under the curve - this is proportional to the total number of viewers (or listeners)

The distributions have been determined for each of these statistics from over 2 years of weekly ARIA charts and from our algorithmically generated charts for a range of values of α and p. Low values of α and p lead to slow moving charts, with individual titles spending long time in the chart. Higher values of α and p lead to faster moving charts with titles moving rapidly up the chart, but turning and falling out of the chart equally rapidly. As a comparison, three values of α and p have been selected for comparison with the ARIA chart statistics. In particular, values of (α,p) that have been used are (0.1,0.1) (termed "slow"), (0.2,0.4) (termed "normal") and (1.0,1.0) (termed "rapid"). The distributions of each statistic discussed above are shown in Figure 3.15, Figure 3.16 and Figure 3.17 respectively.

From the cumulative distributions it is observed that graphically the "normal" algorithmic chart provides a relatively close fit to the ARIA chart in all three statistics considered. Although from a strict statistical viewpoint the goodness-of-fit is not exceptional, the graphs do show that the algorithmic approach exhibits the same trends as the actual ARIA chart statistics. Most importantly, however, the "slow"

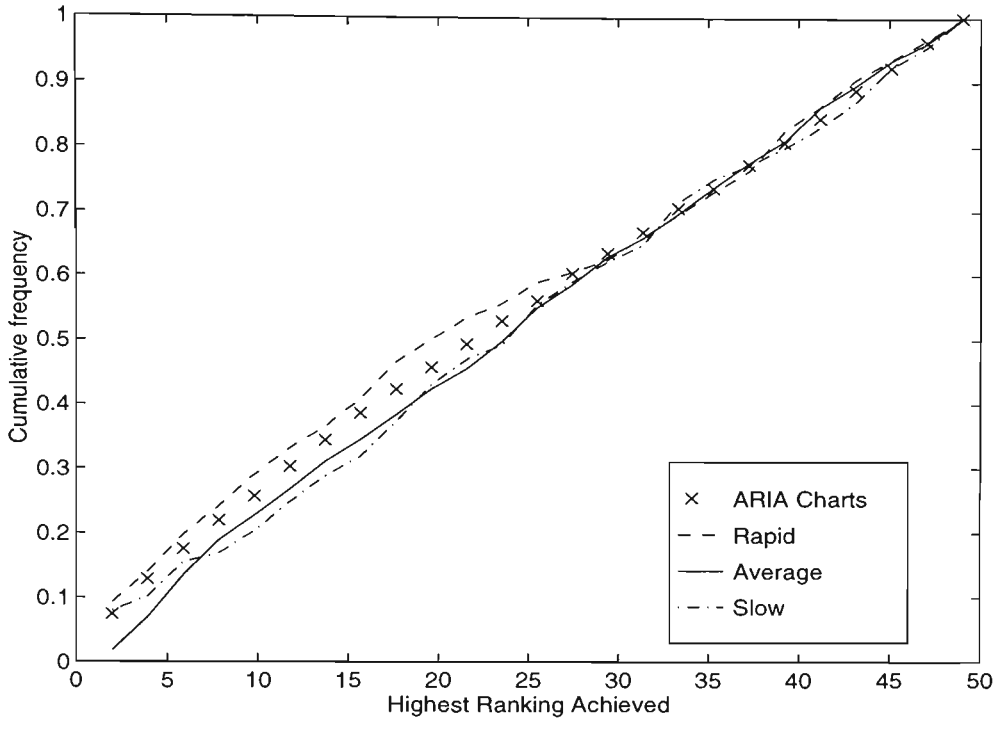


Figure 3.15 Cumulative frequency of highest ranking achieved for ARIA and algorithmically generated charts

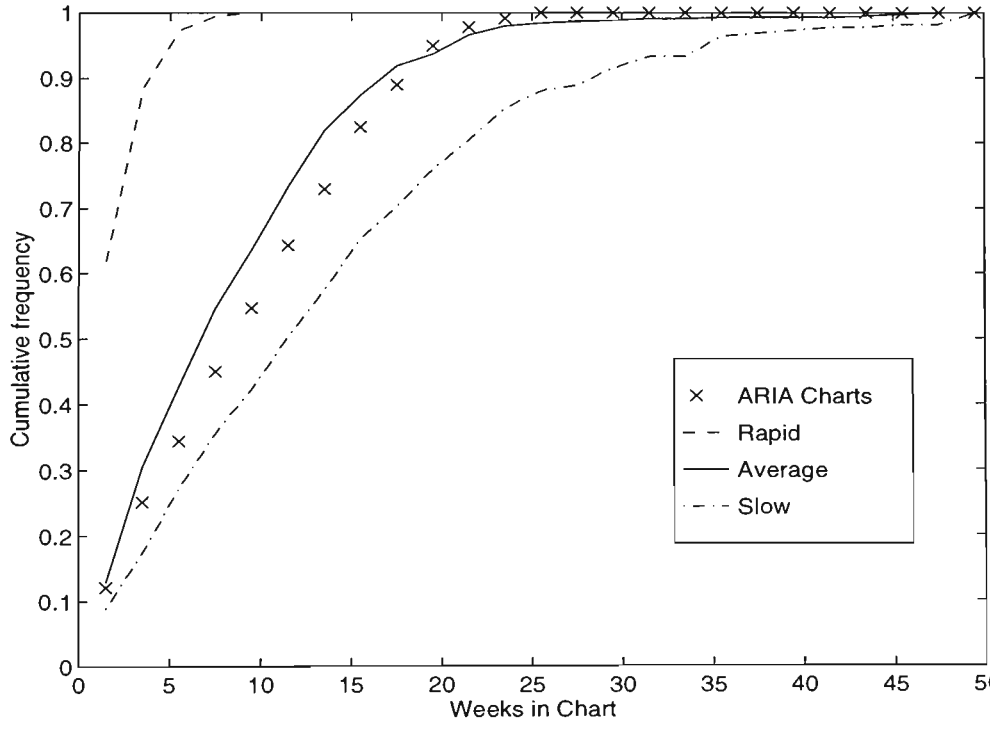


Figure 3.16 Cumulative frequency of weeks in chart for ARIA and algorithmically generated charts

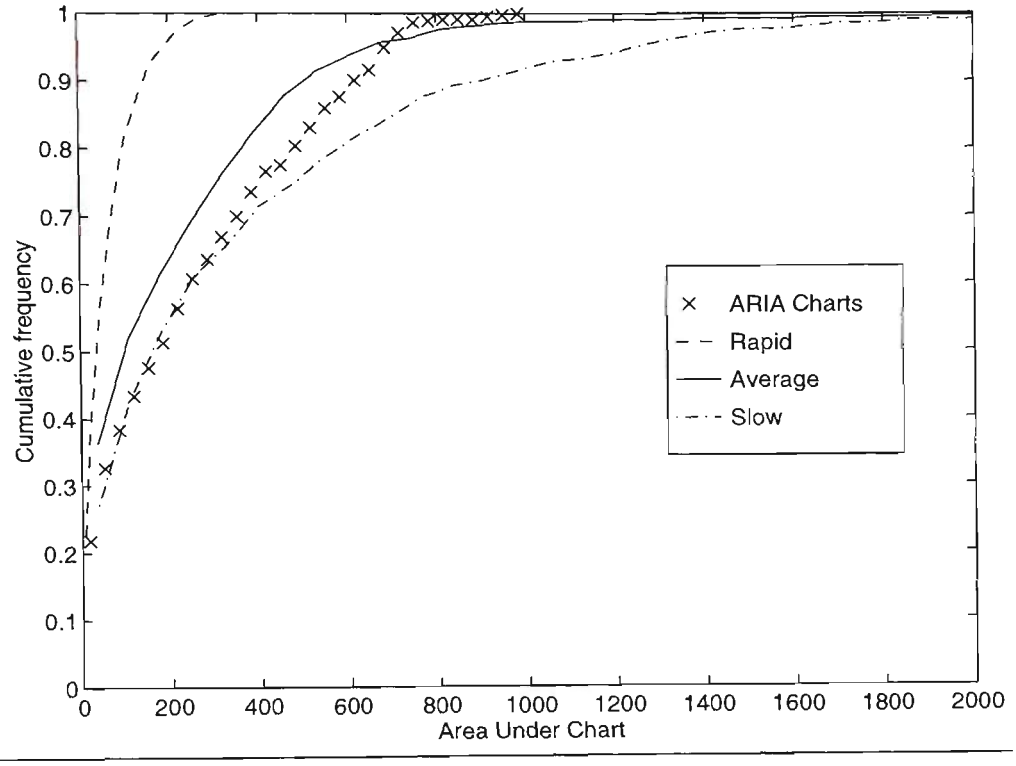


Figure 3.17 Cumulative frequency of area under chart for ARIA and algorithmically generated charts

and "rapid" charts form an envelope which always completely encloses the ARIA (and normal) chart. Hence, by considering the performance of the caching algorithms for all three of the algorithmic chart models shown here, it is likely that the actual performance of the cache will lie within the results obtained. Note that the "slow" and "rapid" charts are aptly named with reference to the distribution of the number of weeks in the chart and the area under the chart. Interestingly, the highest rank distribution is not significantly different for any of the charts. A title (that reaches the Top 50) is almost equally likely to reach number 1 as it is to reach any other position. Although titles in the "rapid" chart spend only a short period of time in the chart, they also move very quickly, implying that they are just as likely to reach high positions as titles in the other charts.

3.6.2 Caching Algorithms

With a realistic model of video movement in place, it is now possible to compare appropriate caching algorithms for use in the FES. Sev-

eral algorithms have been designed and implemented. The algorithms (first proposed in [Barn95b]) are described below. In each case, the amount of space in the cache is sufficient to allow it to hold M movies.

- **Ideal** - The Top M movies are always held in the cache. This is achieved by looking forward into the popularity chart and forms an unachievable best case bound.

- **Static** - The cache contents begin with the initial Top M movies and never change. This effectively forms a worst case bound.

- **More Requests** - When an uncached title with more requests than one currently cached is requests, it is moved into the cache at the expense of the one with the least requests. The cache starts with the Top M movies in place.

- **More Frequent** - If the time between the last two requests for an uncached title is less than that for any of the cached titles then the new title is inserted. Again the cache starts with the Top M movies in place.

- **Moving Average** - Similar to More Frequent, but looks at the interarrival time of a group of requests greater than two and uses the average interarrival time to determine whether replacement should occur.

It is important to note that the replacement of a movie in the cache incurs essentially no overhead (other than the initial transmission of the video from the VS). This is because in each case a replacement only occurs at a time that coincides with the transmission of a request to a customer; and this transmission must by necessity pass through the FES anyway. Also, the movie being deleted is still held in the main video server and so no form of backup or transmission from the FES upstream to the VS is required.

Notice also, that the simplicity of the above algorithms ensures that only a slight computational overhead is incurred at the FES. As such there will be no difficulty with implementing such schemes at each FES in order to ensure that cache contents are kept up to date with the current most popular titles. As the next section will show, even these simple algorithms are capable of achieving this task.

3.6.3 Performance of Caching Algorithms

The above algorithms were all implemented in an event driven simulator with 10,000 customers each connected to a FES in turn connected to a core network with several video servers (VS's). Movie requests are generated with a Poisson arrival distribution. The requested movie is determined by generating a Uniform(0,1) random variable and using Equation 3.8 to map this to a movie rank from the empirical distribution. This rank is translated to an unique video object identifier using the algorithmic approach discussed in Section 3.6.1.

The different caching algorithms are compared based on the percentage of requests that are satisfied at the FES without need to refer to the VS. Note that this is identical to the concept of cache hits traditionally used as a figure of merit for cache systems.

The performance of the algorithms are compared for a variety of cache sizes and a number of different parameters for the input charts. As already seen, when the values of α and p are changed, the charts become faster or slower moving. We evaluate the algorithms for both "rapid" and "slow" moving charts as well as the "normal" case that best matches the ARIA chart. Figure 3.18 shows the results for the "normal" chart for various policies for cache sizes ranging from 1 to 200 movies.

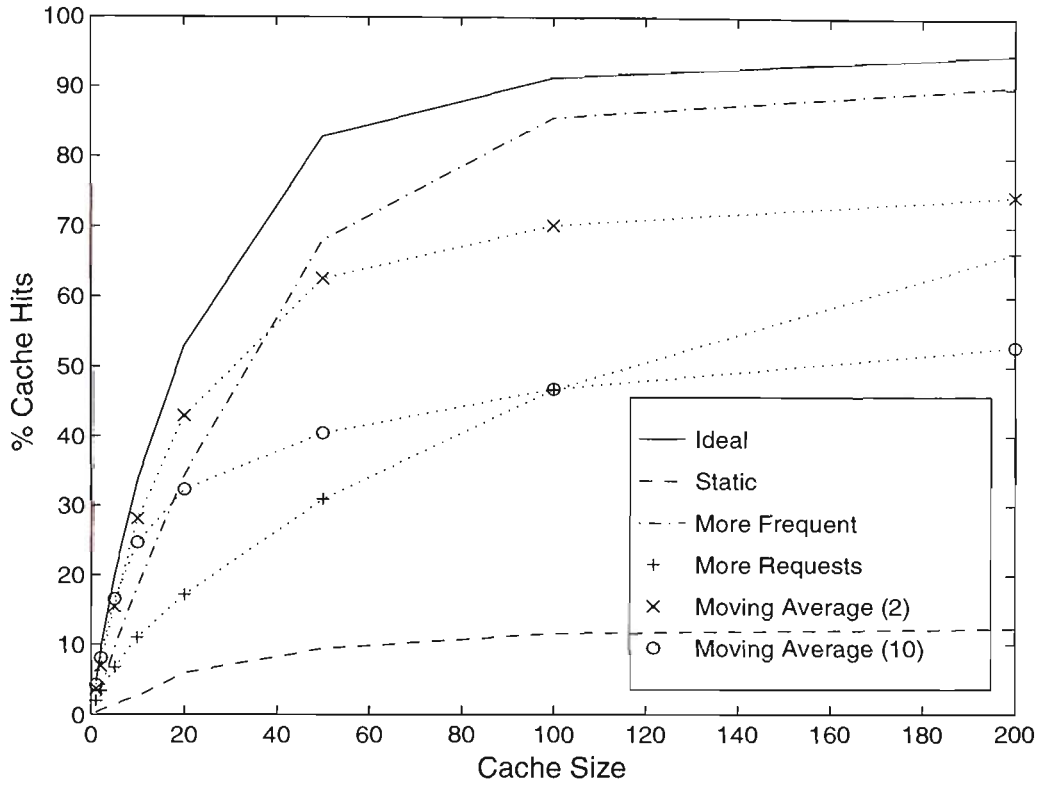


Figure 3.18 Cache performance for various policies

Note that in all graphs the 95% confidence intervals[5] were within 5% of the values shown and as such error-bars are omitted from the diagrams to aid clarity. From the graphs above we see that the Ideal algorithm follows the video popularity distribution shown in Figure 3.5. This is to be expected as it provides perfect caching always storing the Top M movies. The results of Figure 3.18 imply that for cache sizes above about 40 movies the More Frequent policy performs best, being within 10% of the ideal case at higher cache sizes.

At lower cache sizes we see that the Moving Average algorithm performs quite well (see Figure 3.18). This is due to the large number of requests being received for all the movies in these small caches. As caches become larger, the number of requests being received for the less popular movies is smaller, and so it takes longer for the moving

5. Throughout this dissertation, confidence intervals of simulation based results are calculated using the method of "batch means" as discussed in [Law91].

average to adjust (especially with larger window sizes). Effectively the moving average algorithm takes too long to "realise" that a movie has become popular and the movie is possibly already descending the chart again by the time it has been moved into the cache.

The More Requests algorithm performs quite poorly due to the fact that it essentially caches the most popular movies of all time. For example, current contents of the cache may include "E.T.", "Casblanca" and "Gone with the Wind" even though these movies are no longer particularly popular.

As expected the Static algorithm performs very poorly, as it never adjusts to the changing popularities of videos with time.

Results from the More Frequent Algorithm are encouraging. As discussed above, it performs within about 10% of Ideal at cache sizes of between 70 and 100 movies and is straightforward to implement.

In the next section we evaluate the performance of the algorithms in faster and slower moving charts than those used above.

3.6.3.1 Sensitivity Analysis

The charts used above were selected to be the best match to the available ARIA chart data. It is possible that video charts will move more or less rapidly than these. In order to determine the sensitivity of the algorithms to these changes, we have examined "slow" charts (alpha=0.1, p=0.1) and "rapid" charts (alpha=1.0, p=1.0). The effect that the change in parameters has on the charts is shown in Figure 3.15, Figure 3.16 and Figure 3.17.

Following this change in the input chart parameters, it is observed that all algorithms perform better in a chart that changes more slowly, which is to be expected. Importantly, the More Frequent algorithm still performs quite well in the fast moving chart where the other algorithms degrade quite badly (refer to Figure 3.19 and Figure 3.20).

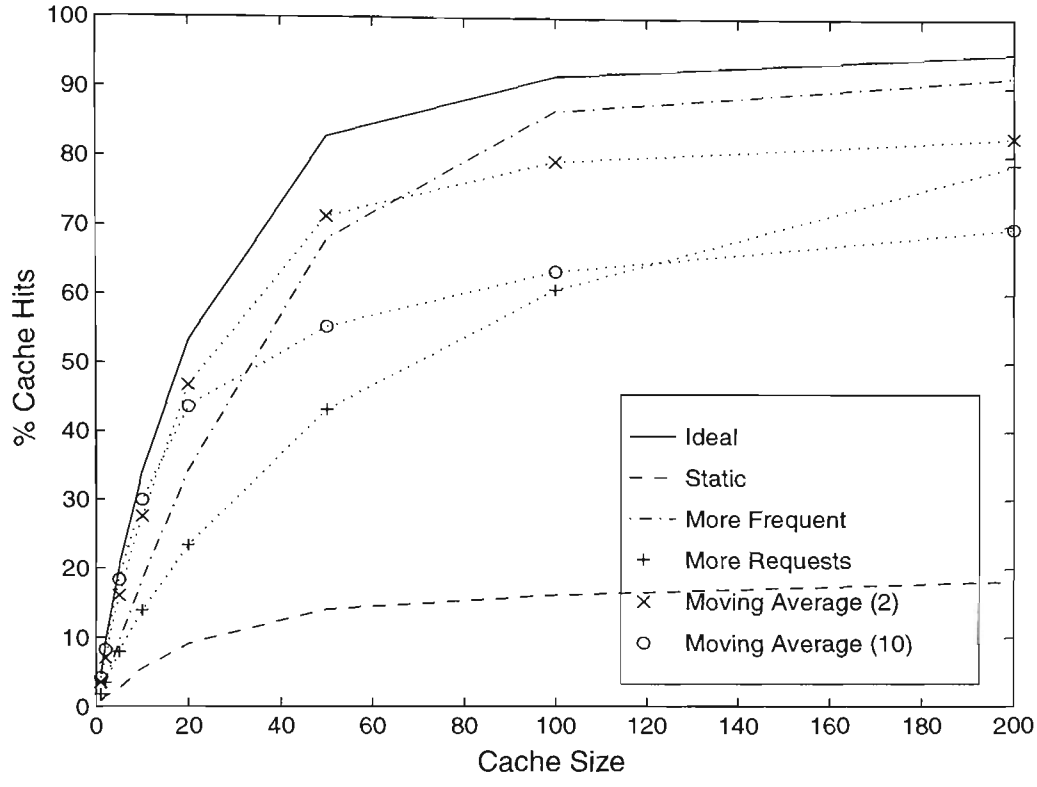


Figure 3.19 Cache performance for slowly moving charts

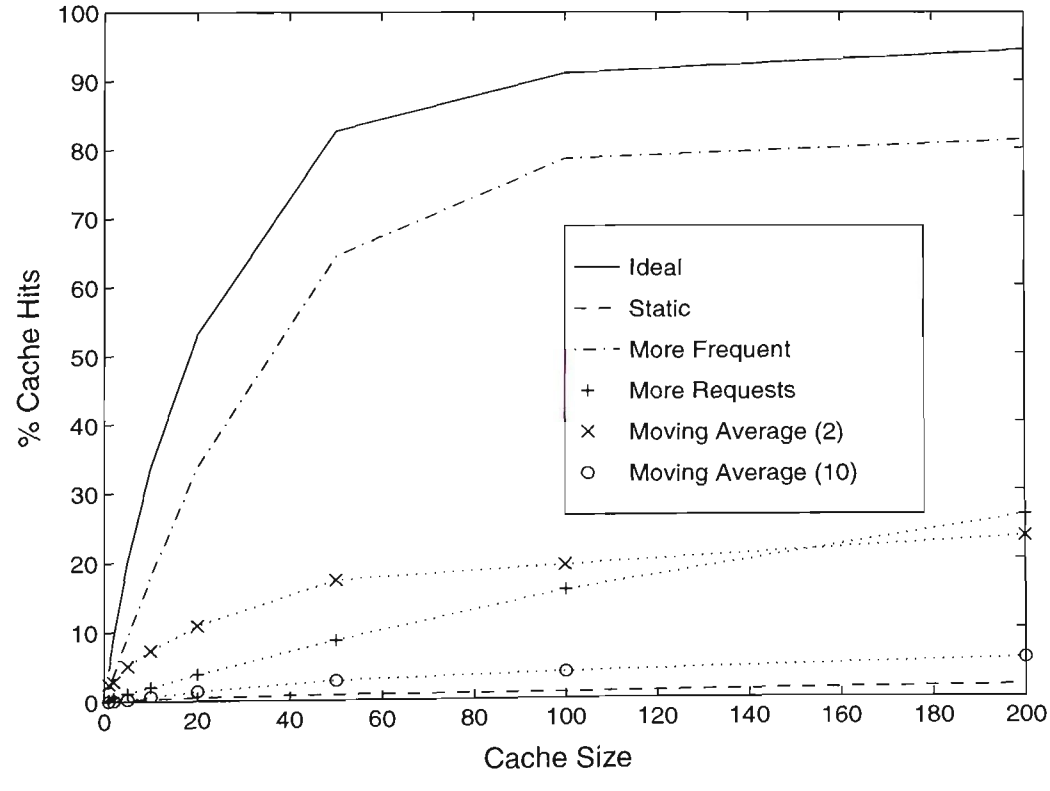


Figure 3.20 Cache performance for rapidly moving charts

Although it is possible that further improvements could be made to the algorithms identified here, emphasis should be given to the fact that computationally simple algorithms can be shown to perform very well in a variety of realistic situations. This would indicate that effective caching can be performed at Front-End Servers, despite the sometimes rapidly changing video popularities.

3.7 Conclusion

This chapter has considered interactive video network design. Specifically, the issue of distributed versus centralised approaches to storage have been discussed with reference to realistic server architectures and cost models. Earlier, similar analyses have used elegant but unrealistic assumptions regarding server cost and numerous simplifying assumptions concerning the topology of the core network. Our approach developed a server cost model based on a realisable hardware architecture and eliminated network costs from the analysis. Incorporating network costs would only serve to reinforce our conclusions regarding the efficiency of distributed approaches to storage.

A detailed model of server cost was developed early in the chapter. This required models for disk cost and video popularity which were derived and validated against empirical data. Analysis of the resulting model revealed that the highly skewed video popularity distribution leads to resource wastage in an homogeneous storage system consisting of a single type of disk. This lead to the proposal of an heterogeneous storage system [Barn96c] which maintains the advantages of previously proposed hierarchical storage systems but without the disadvantages of RAM and tape storage.

Optimisation of this realistic heterogeneous approach lead to system costs which were comparable to the demonstrable lower bound given by the "ideal" heterogeneous system, initially derived. With a realis-

tic model of system cost in hand, centralised and distributed approaches to storage were compared in terms of cost per stream. For a given set of assumptions, it was demonstrated that a distributed approach actually costs less in terms of storage than the centralised equivalent. Further, for the circumstances considered, it was shown that a cache located at the FES should be dimensioned such that it aims to serve approximately 90% of the total number of user requests for the popularity distribution presented here.

Given that a distributed architecture results in the minimal cost, the final section of the chapter has developed and analysed several caching algorithms suitable for use in a FES of a distributed interactive video system. Chart movement was generated algorithmically and validated against actual chart data obtained from the music recording industry. This movement data was then used to evaluate the caching algorithms proposed. It was seen that a simple caching scheme based on request interarrival times for each particular title is efficient and maintains a high ratio of cache hits, even in relatively fast moving charts.

Several important conclusions arise from this chapter.

- The FES is a logical place for the placement of video buffers (caching) since considerable functionality is already required there.
- Magnetic disk cost can be modelled as a linear function of capacity, with no clear correlation between cost and speed.
- Video popularity is difficult to accurately model due to a lack of empirical data. Existing data indicates that the commonly used Zipf distribution may not be suitable for large numbers of objects. This is confirmed by the large number of different popularity models in used (see Chapter 2).
- Disk based video servers can be particularly inefficient if not designed carefully, accounting for both storage and bandwidth requirements of individual objects.

- For a given server implementation, distributed storage is economically more viable than centralised storage. This reinforces the results of Nussbaumer and Tetzlaff which were made under considerably different assumptions.

- Simple caching algorithms provide adequate performance to cater to the changing popularities of objects typically encountered in an interactive video system.

Following from these conclusions the next chapter considers the use of disk arrays in video servers in more detail. Specifically the reliability of a disk array is investigated and a performability analysis is used to determine the most efficient "level" of RAID to use for interactive video applications.

4. Interactive Video Server Design

The best is the cheapest.

- Benjamin Franklin

4.1 Introduction

Video servers form the heart of an interactive video network. As well as providing high storage and throughput capacities, video servers must be highly reliable to ensure customer satisfaction. With this in mind, this chapter focuses on the efficient and reliable design of such video servers. As seen in Chapter 3, many of these servers will be deployed in a large-scale interactive video network. Hence, low cost and high reliability are essential in any server design.

Section 4.2 briefly revisits the idea of storage hierarchies proposed to solve the problems caused by the extremely skewed video popularity distribution. The drawbacks of such hierarchies are reiterated, and the benefits of disk arrays clarified. Section 4.3 considers disk arrays in detail, particularly examining the relevant levels of RAID used to provide redundancy and improve reliability. From the 7 levels of RAID, levels 3 and 5 are found to be most suitable. This conclusion is in agreement with the literature where both levels are advocated by different authors (see Section 2.4.7). In an effort to alleviate the apparent confusion between the two, the trade-offs are discussed in detail in the rest of the chapter. A cost comparison of RAID 3 and RAID 5 is performed in Section 4.4, while performability of each array type is analysed using discrete-time Markov Reward

Models in Section 4.5. Combining the cost and reliability models of the previous sections, Section 4.6 shows the results of several case studies, comparing the suitability of RAID 3 and RAID 5 arrays under a range of conditions. Section 4.7 draws the conclusion that RAID 5 is superior for a broad range of operating conditions.

4.2 Storage Hierarchies

Video servers are essentially massive I/O machines, responsible for maintaining a large number of high-bandwidth streams for long periods of time. As already mentioned, these servers will require thousands of gigabytes of storage capacity and thousands of megabits per second of bandwidth. As discussed in Chapter 2, there are a number of approaches to meeting these requirements. Perhaps the most intuitive approach involves the use of a storage hierarchy, whereby popular movies requiring larger bandwidths (due to the greater number of viewers) are allocated to correspondingly higher bandwidth storage such as RAM. Similarly, unpopular movies are potentially archived on slow but cheap optical disk or tape storage. Such systems are discussed in [Barn96c] [Barn95a] [Doga94b] [Lau95b] [Stol95] in various different guises. The limited flexibility and scalability of such hierarchical systems is problematic and their general utility in the field of video services is open to debate. The use of disk arrays for the entire storage requirements can potentially overcome the need for hierarchical storage, since large disk arrays are able to satisfy the high bandwidth requirements of popular movies even for large customer populations. Efficiently utilising disk arrays for unpopular movies is also an important issue. Chapter 3 presented an efficient heterogeneous scheme for allocating movies to disk arrays using different disk capacities to form a sort of storage hierarchy. In Chapter 5 we develop an efficient heuristic for the use of homogeneous disk arrays which stores unpopular movies cost effectively by utilising resources that would otherwise be unused by

the popular titles. Using this approach a video server will consist of a number of identical disk arrays each storing a subset of the total set of movies.

4.3 Disk Arrays

The architecture of a video server based on multiple disk arrays is shown in Figure 4.1.

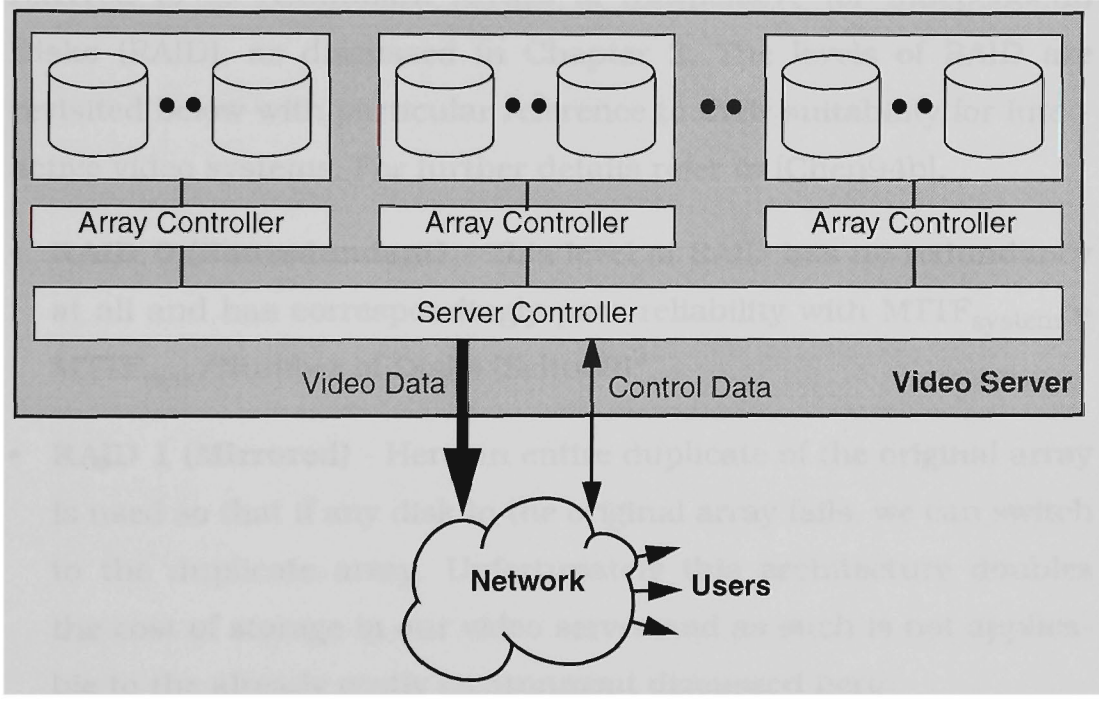


Figure 4.1 A disk array based video server architecture

Large disk arrays seem able to meet the performance demands of most interactive video applications. Although considerable work has been done to show that such arrays are indeed capable of providing the high performance (measured in terms of throughput) to satisfy these requirements (see Section 2.4.2), little has been done to show that the availability[1] of the video server will match it's performance.

1. In this thesis the term "availability" is used to represent the proportion of time that a server is fully operational.

4.3.1 Reliability Problems and RAID

In addition to having a high storage capacity and bandwidth, a video server must be reliable. It must meet some minimum requirement for the percentage of time it is available to serve customers requests, without requiring constant maintenance. Various redundancy schemes are available to help meet this requirement but they vary in their efficiency during the various modes of operation and also in their cost. The various mechanisms are all classified into a group referred to as Redundant Arrays of Inexpensive (or Independent) Disks (RAID), as discussed in Chapter 2. The levels of RAID are revisited below with particular reference to their suitability for interactive video systems. For further details refer to [Chen94b].

- **RAID 0 (Nonredundant)** - This level of RAID has no redundancy at all and has correspondingly poor reliability with $MTTF_{system} = MTTF_{disk}/\text{Number of Disks}$ [Schu89][2].

- **RAID 1 (Mirrored)** - Here an entire duplicate of the original array is used so that if any disk in the original array fails, we can switch to the duplicate array. Unfortunately this architecture doubles the cost of storage in our video server and as such is not applicable to the already costly environment discussed here.

- **RAID 2 (Memory-Style ECC)** - This level uses Hamming codes to be able to detect and repair a single bit error. Even without knowledge of which disk has failed, the system can repair the data in real-time. This is largely unnecessary in modern disk arrays since the array controller can identify which disk has failed. Again the cost is high with the number of redundant disks equal to the logarithm of the number of data disks.

- **RAID 3 (Bit-Interleaved Parity)** - Operates similarly to RAID 2 but relies on knowledge of which disk in the group has failed and uses a single parity disk to rebuild the data. This approach uses

2. MTTF = Mean Time To Fail

fine-grained striping (see Section 2.4.2) to service requests. The cost here is minimal as only a single additional disk is required regardless of the array size.

- **RAID 4 (Block-Interleaved Parity)** - Similar to RAID 3 except data is interleaved across disks in blocks of an arbitrary size (rather than bitwise as in RAID 3). Again the cost is only that of a single disk per group.

- **RAID 5 (Block-Interleaved Distributed-Parity)** - RAID 4 has a bottleneck at the parity disk since it must be accessed for every write to any data disk. This effectively decreases throughput under heavy write workloads. RAID 5 overcomes this problem by distributing parity and data among all disks in the group. This effectively removes the idea of a normally dormant parity-only disk, but retains the ability of the system to recover from a single failure. RAID 5 is entirely superior to RAID 4, and is often the preferred level for standard file system applications. This approach is effectively coarse-grained striping (see Section 2.4.2) with distributed parity.

- **RAID 6 (P + Q Redundancy)** - This is essentially an extension of RAID 5 with another redundant disk coded in such a way that the system can now withstand two disk failures. This could be important in extremely large arrays or where data integrity is critical. Clearly there is an increase in cost (of one disk) from the RAID 5 approach, although for large arrays, this cost increase is negligible. There has, however, been little support for the deployment of RAID 6 arrays in industry. This is presumably due to higher implementation complexity and due to the satisfactory performance of lower levels of RAID. For this reason, RAID 6 is not considered further in this thesis.

For reasons discussed above RAID 3 and RAID 5 are considered as the two most suitable candidates for video servers. The only difference between these approaches is that RAID 3 uses fine-grained

striping, while RAID 5 uses coarse-grained striping. This difference is discussed in the next section.

4.3.2 Striping in Disk Arrays

The primary advantage of disk arrays is their ability to increase both capacity *and* bandwidth with only a linear increase in cost. This advantage is gained through disk striping. Disk striping involves placing data across a number of disks rather than just on a single disk. In a traditional[3] file system, for example, a 10MB file might be spread across 10 disks with 1MB allocated to each disk. Clearly, if the only request being serviced is for this file and the architecture supports it, this file can be retrieved in about 1/10th of the time (with fine-grained striping) that it would take if stored on a single disk. Disk striping schemes can be categorised into two types: fine-grained and coarse-grained. Section 2.4.2 discussed these two schemes in some detail.

From a RAID perspective fine-grained striping corresponds to RAID 3 while RAID 5 implements coarse-grained striping. This difference has important consequences. In RAID 5, the block size on each disk is the same as the block size requested by the user. In fine-grained striping (RAID 3) the block size requested by the user is a factor of D times larger than the block size of each disk (where D is the number of disks in the group). Figure 2.7 (reproduced in Figure 4.2) serves to illustrate this key difference between fine and coarse grained striping. As will be shown in the next section, this difference in block size has a large effect on the efficiency of the disk array.

3. Here, "traditional" refers to computer systems which have rapid data retrieval as their goal. Prior to multimedia applications most computer systems could be described in this way.

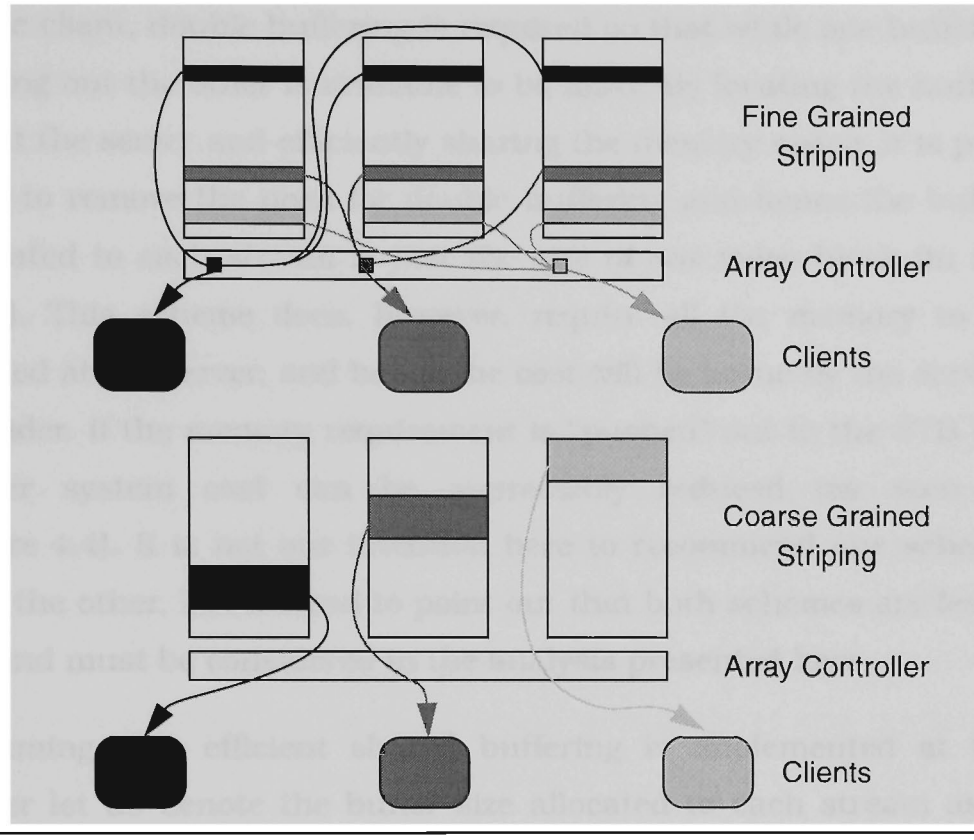


Figure 4.2 Comparison of fine and coarse grained striping

4.4 Cost of RAID 3 vs RAID 5

This section investigates the cost of implementing a RAID 3 or RAID 5 video server capable of supporting the same peak load. Disk block size selection has a large effect on the throughput capabilities of magnetic disk drives. Further to this, the choice of RAID level (3 or 5) directly effects this block size.

If we assume that a certain buffer exists in the Set-Top Box (STB) at the customers premises, then a single video block[4] (the block retrieved in each service cycle) cannot exceed this buffer size. It is actually likely that this buffering will be provided within the video-server, with only smaller "dejittering" buffers at the STB. As shown in [Toba93], this approach ideally allows effective memory sharing to alleviate the need for double buffering [Mour96]. With buffers located

4. Note that a "video block" is the amount of data retrieved during each round, while a "disk block" is the amount of data retrieved contiguously from a single disk. Only in the case of RAID 5 are they equivalent.

at the client, double buffering is required so that while one buffer is playing out the other is available to be filled. By locating the buffering at the server and efficiently sharing the memory space, it is possible to remove the need for double buffering and hence the buffer allocated to each stream is just the size of one video block (in the limit). This scheme does, however, require all the memory to be located at the server, and hence the cost will be borne by the service provider. If the memory requirement is "pushed" out to the STB the server system cost can be appreciably reduced (as seen in Figure 4.4). It is not our intention here to recommend one scheme over the other, but instead to point out that both schemes are feasible and must be considered in the analysis presented here.

Assuming that efficient shared buffering is implemented at the server let us denote the buffer size allocated to each stream as B bytes and hence a video block is also B bytes[5]. The number of video blocks required by a given movie is governed by its length. Let us assume a particular video requires M blocks. So, clearly B*M is the total storage capacity required by the movie (in bytes). If a disk array with D disks is used to store this movie, the actual disk block size will depend on the type of striping used. For fine-grained striping, each disk will have M blocks, but the size of each block will be B/D bytes, since all disks are accessed for all requests. For coarse-grained striping each disk will have M/D blocks of size B bytes. Clearly, for a given video block size, coarse grained striping results in larger disk block sizes, which as presented below, leads to improved disk throughput.

4.4.1 Throughput vs Block Size

When servicing a request, a disk goes through several phases in order to read the data. The heads must move from their current location to the start of the data (seek time), the disk must rotate

5. In the case where double-buffering is used, the buffer size would be 2B per stream, but the argument presented still applies.

until the start of the data is under the head (rotational latency)[6], the data must be read at a rate determined by the time per revolution, with the head seeking to the next track once each track is read (or performing a head switch to another track in the same cylinder); this continues until the entire disk block has been read. As such, the *sustainable throughput* of a single disk drive can be determined as the amount of data read divided by the time it takes to read it plus the delay incurred by overheads such as seeking and rotational latency (see Equation 4.1). We don't model such things as bus contention between disks since (as stated in Chapter 2) we assume a non-blocking high-bandwidth interconnect such as ATM. Similar models of disk throughput have been used in the past by various authors to account for the mechanical overheads of disk operation ([Chan94b] [Chen93] [Rama95] [Vin94a]). The sustainable throughput of a disk is thus governed by a number of factors as shown below. Note that definitions of all symbols used in this chapter can be found in Table 4.1, although they are also described as they occur.

$$R_D = \frac{N_T C_T}{\lceil N_T \rceil (t_r + t_{s1}) + t_{sa} + t_l - t_{s1}} \qquad \text{(Eqn 4.1)}$$

where R_D = sustainable throughtput (bytes/second)
N_T = number of tracks per block
C_T = capacity of a single track (bytes)
t_{s1} = track-to-track seek time (seconds)
= (assumed equal to head-switch time)
t_{sa} = average seek time (seconds)
t_l = rotational latency (seconds) = $t_r/2$
t_r = time for one revolution (seconds)

The ceiling function in Equation 4.1 rounds up the number of seeks and latencies to the next highest integer. This implies that the most efficient read size is an integral number of tracks as this minimises

6. Rotational latency can actually be eliminated by the use of "On Arrival Caching" [Cohe95], otherwise known as Zero Latency Read which is applicable when reading multiple tracks in a single block. This requires hardware support at the disk level and so will not be assumed here.

Table 4.1 Definition of symbols used in Chapter 4

Symbol	Definition
B	video buffer size (bytes)
M	number of blocks per video
D	number of disks in an array
R_D	throughput of a single disk (bytes/sec)
R	throughput of a disk array (bytes/sec)
N_T	number of disk tracks per video block
C_T	capacity of a single disk track (bytes)
t_{s1}	track-to-track seek time (secs)
t_{sa}	average seek time of a disk (secs)
t_l	average latency (secs)
t_r	time for one rotation of a disk (secs)
t_1	t_r+t_{s1}
t_2	$t_{sa}+t_l-t_{s1}$
K_D	cost of a single disk ($) = $K_1 + K_2*C_D$
K_1	fixed part of disk cost ($)
K_2	variable part of disk cost ($ / GB)
C_D	capacity of a single disk in an array
C	total capacity of RAID array.
K_B	cost per byte of buffer ($/byte)
R_l	average rate of a single video stream (bytes/sec)
K	total cost of a disk array and buffering ($)
Re	reward structure for disk array
p	number of columns in reward structure (typically 24)
$r_{i,\ t \bmod p}$	reward rate in state i at time t
λ_s	failure rate of a single disk = 1/MTTF
λ'	$(D-1)\lambda_s$
λ	$D\lambda_s$
μ	rebuild rate of an array after a single disk failure = 1/MTTR(1)
μ'	rebuild rate of an array after a total failure = 1/MTTF(F)
$P_0(t)$	probability of being in state 0 at time t
$P_1(t)$	probability of being in state 1at time t
$P_2(t)$	probability of being in state 2 at time t
Z(t)	state of Markov Chain at time t
X(t)	instantaneous reward earned at time t, $X(t) = r_{Z(t),\ t \bmod p}$
Y(t)	total accumulated reward up until time t
n	number of discrete time units in t, $n = t/\Delta t$

the overhead caused by seeking and latency. Clearly there is an overhead incurred by the seek and rotational latency of the disk for every block retrieved. This overhead is minimised by retrieving a small number of large blocks as is the case with coarse-grained striping.

Before continuing the discussion, we simplify the notation of Equation 4.1 as follows:

$$R_D = \frac{N_T C_T}{\lceil N_T \rceil t_1 + t_2} \quad \text{(Eqn 4.2)}$$

where $t_1 = t_r + t_{s1}$

and $t_2 = t_{sa} + t_l - t_{s1}$

Now the number of tracks read from each disk depends on the video buffer size B and the number of disks in the array D. For the remainder of the analysis it is assumed that the number of tracks read for each block is chosen to be integral and so the ceiling function in Equation 4.1 and Equation 4.2 is no longer required. The number of tracks read per block is given by:

RAID 3: $$N_T = \frac{B}{DC_T} \quad \text{(Eqn 4.3)}$$

RAID 5: $$N_T = \frac{B}{C_T} \quad \text{(Eqn 4.4)}$$

As expected, the size of the disk blocks used in a coarse grained approach are larger by a factor of the number of disks in the array than the block size used with fine-grained striping.

The expected throughput from a RAID 3 and RAID 5 array can now be written in terms of the video buffer size B and the number of disks in the array as well as the disk related parameters. (Notice that R_3 and R_5 give the array throughput, whereas R_D is the throughput of each disk in the array).

RAID 3: $$R_3 = \frac{B}{(B/(DC_T))t_1 + t_2} \quad \text{(Eqn 4.5)}$$

RAID 5: $$R_5 = \frac{BD}{(B/C_T)t_1 + t_2} \quad \text{(Eqn 4.6)}$$

It should be noted that in RAID 3, throughput may actually be slightly less than that shown in Equation 4.5 due to the fact that all disks must remain synchronized. We don't attempt to model this slight penalty here, instead assuming that all disks will remain perfectly synchronized during operation.

We can now rearrange Equation 4.5 and Equation 4.6 to determine the disk requirement for a particular sustainable throughput requirement R from a RAID 3 or RAID 5 disk array. We add a subscript to the D to distinguish between the two different cases under consideration.

RAID 3:
$$D_3 = \frac{RBt_1}{C_T(B - Rt_2)} \quad \text{(Eqn 4.7)}$$

RAID 5:
$$D_5 = \frac{Rt_1}{C_T} + \frac{Rt_2}{B} \quad \text{(Eqn 4.8)}$$

Using Equation 4.7 and Equation 4.8 we can determine the number of disks required for both RAID 3 and RAID 5 disk arrays to support an equivalent peak load, for a fixed video buffer size. The choice of buffer size will effect the number of disks required and as such effect the overall system cost. In both cases a larger buffer size leads to decreased disk requirements due to the improved throughput obtainable. To determine the total cost of either system we must account for disk and buffering requirements. The cost functions for RAID 3 and RAID 5 disk arrays are shown in Equation 4.9 and Equation 4.10.

RAID 3:
$$K_3 = D_3 K_{D3} + \frac{K_B B_3 R}{R_1} \quad \text{(Eqn 4.9)}$$

RAID 5:
$$K_5 = D_5 K_{D5} + \frac{K_B B_5 R}{R_1} \text{ o} \quad \text{(Eqn 4.10)}$$

where K_{D3} and K_{D5} are the costs per disk for RAID 3 and RAID 5 arrays respectively, K_B is the cost per byte of buffering and R_1 is the bandwidth of a single stream such that R/R_1 gives a measure of the number of customers (and the number of buffers of size B required).

Note that K_{D3} and K_{D5} differ since the disk capacity and hence cost per disk in the RAID 3 and RAID 5 systems are different.

In order to ensure a fair comparison of the two systems, it is essential that both throughput and capacities are equal. Equation 4.7 and Equation 4.8 determine the appropriate number of disks to ensure that the throughputs are equal, but we must introduce a constraint to ensure capacities of the two arrays are equal. This is achieved by selecting the disk capacity for each case according to some total capacity requirement, C.

RAID 3: $$C_{D3} = C/D_3 \quad \text{(Eqn 4.11)}$$

RAID 5: $$C_{D5} = C/D_5 \quad \text{(Eqn 4.12)}$$

Now, the cost per disk can be determined from the capacity using a linear model with an offset as derived in Chapter 3 (Equation 3.5).

RAID 3: $$K_{D3} = K_1 + C_{D3}K_2 \quad \text{(Eqn 4.13)}$$

RAID 5: $$K_{D5} = K_1 + C_{D5}K_2 \quad \text{(Eqn 4.14)}$$

Substituting Equation 4.11 and Equation 4.12 into Equation 4.13 and Equation 4.14, and then along with Equation 4.7 and Equation 4.8 into Equation 4.9 and Equation 4.10 the cost functions are obtained.

RAID 3: $$K_3 = \frac{K_1 R B_3 t_1}{C_T B_3 - C_T R t_2} + K_2 C + \frac{K_B B_3 R}{R_1} \quad \text{(Eqn 4.15)}$$

RAID 5: $$K_5 = \frac{K_1 R t_1}{C_T} + \frac{K_1 R t_2}{B_5} + K_2 C + \frac{K_B B_5 R}{R_1} \quad \text{(Eqn 4.16)}$$

To determine the buffer size which minimises cost in either system differentiate equations Equation 4.15 and Equation 4.16 with respect to B_3 or B_5 and solve dK/dB = 0. Differentiating gives:

RAID 3: $$\frac{dK_3}{dB_3} = \frac{K_1 R t_1}{C_T B_3 - C_T R t_2} - \frac{K_1 R B_3 C_T t_1}{(C_T B_3 - C_T R t_2)^2} + \frac{K_B R}{R_1} \quad \text{(Eqn 4.17)}$$

RAID 5: $$\frac{dK_5}{dB_5} = -\frac{K_1 R t_2}{B_5^{\,2}} + \frac{K_B R}{R_1} \quad \text{(Eqn 4.18)}$$

Equating these expressions to 0 and solving for B in each case leaves the expression for optimum buffer size:

RAID 3:
$$B_3 = Rt_2 + \sqrt{\frac{K_1 R R_1 t_1 t_2}{K_B C_T}} \quad \text{(Eqn 4.19)}$$

RAID 5:
$$B_5 = \sqrt{\frac{K_1 R_1 t_2}{K_B}} \quad \text{(Eqn 4.20)}$$

In both cases two solutions are actually obtained but by determination of the second derivative, the appropriate (ie. minimal cost) solution can be ascertained leaving the results shown in Equation 4.19 and Equation 4.20. Notice that in the case of RAID 5, the optimal buffering requirements are independent of R, the required throughput. This is because block size on each disk of a RAID 5 is always equal to the buffer size, regardless of the number of disks in the group. In RAID 3, however, the buffer size is required to increase with R in order to keep the block size on each disk sufficiently large to gain acceptable array throughput.

Substituting Equation 4.19 and Equation 4.20 back into Equation 4.15 and Equation 4.16 yields a complete solution for the minimum cost of RAID 3 and RAID 5 systems of equivalent throughput and storage capacity. The above equations can also be used to derive the number of disks required, the necessary capacity of each disk, and the appropriate buffer size per stream, for a given set of parameters and requirements.

We conclude this section with a comparison of total costs (disks plus buffering) of both RAID architectures for a range of desired throughputs. The following table shows the values used for each of the parameters in the following comparison.

The curves in Figure 4.3 show the difference in cost for RAID 3 and RAID 5 for a range of viewers (from 1 to 500) and for the parameter values shown in Table 4.2. The curves shown represent the sum of disk and buffering costs for the minimum cost system as determined

Table 4.2 Default parameter values (disk related parameters are from the Maxtor 71260A 1.2 GB disk drive)

Parameter	Value	Units
C_T	51,000	bytes
t_1	0.0153	seconds
t_2	0.0167	seconds
R_1	375,000	bytes / second
C	100	GB
K_1	188	$
K_2	275	$ / GB
K_B	50	$ / MB

from Equation 4.15 and Equation 4.19 for RAID 3 and Equation 4.16 and Equation 4.20 for the RAID 5 system.

Notice that as the number of streams approaches zero the cost of both systems asymptotically approaches $27,500. This is because of the requirement to provide 100GB of storage. The cheapest storage costs K_2 dollars per gigabyte (the offset of K_1 becomes negligible) and since K_2 is assumed to be $275 (see Equation 3.5), the result follows. We also see from the graph that there is an increasing difference between RAID 3 and RAID 5 in terms of the minimum cost configuration as the number of viewers supported by the array increases. Indeed for anything above about 250 streams the RAID 3 array is more than double the price of the RAID 5 with equivalent throughput. A RAID 3 array capable of servicing 500 streams costs four times as much as a RAID 5 array with the same capability. This large difference is predominantly due to the buffering costs, since RAID 3 systems require much larger buffers in order to maintain high throughput. Figure 4.4 shows the division of costs between disk and buffering for each of RAID 3 and RAID 5.

Figure 4.4 is of particular interest when it is considered that the buffering may be located in the STB or in the server itself. As such, the cost of buffering may be borne either by the service provider or by the customer. As can be seen from Figure 4.4 the cost of the two

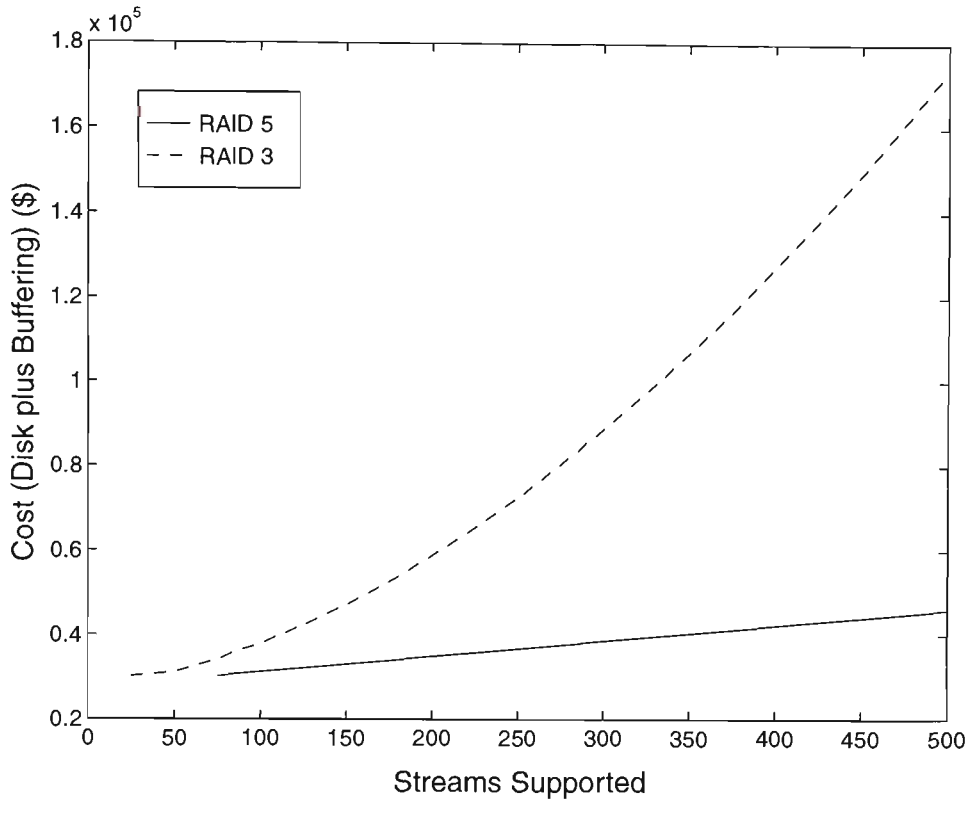


Figure 4.3 Cost of RAID 3 and RAID 5 implementations

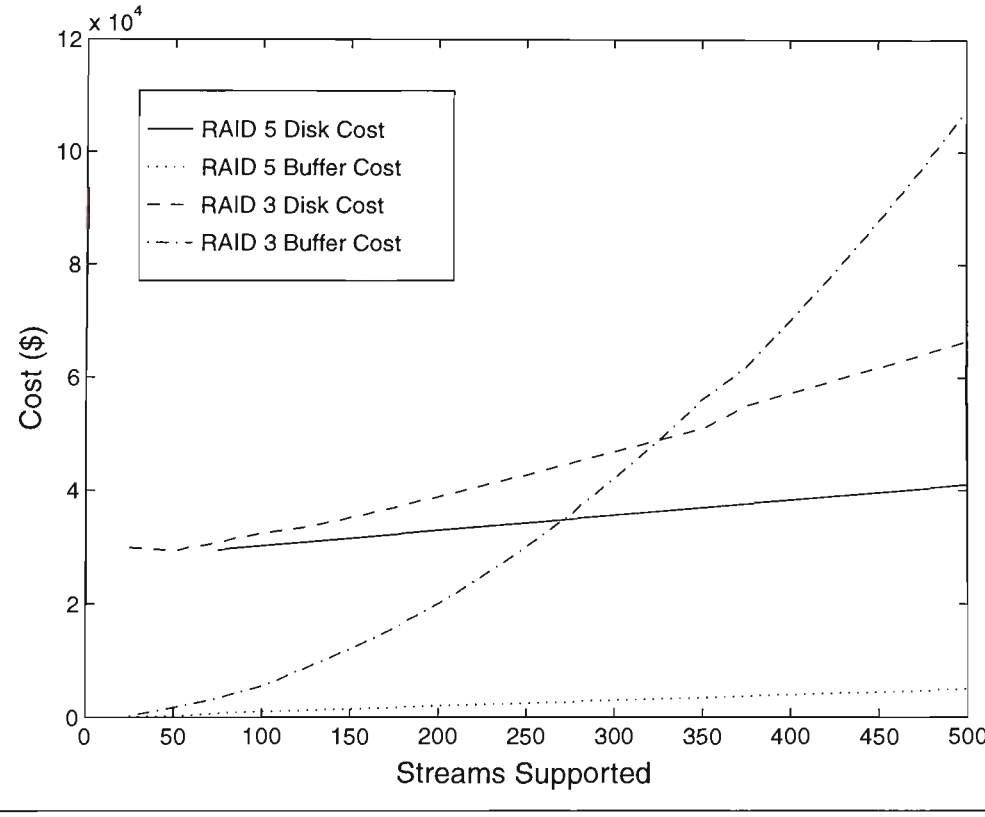


Figure 4.4 Cost of RAID 3 and RAID 5 disk and buffering

systems are much closer together if only disk cost is relevant. Of course the results shown in Figure 4.3 and Figure 4.4 are affected by variation of the parameters shown in Table 4.2, but the parameters used are typical.

In this section it has been shown that, based on reasonable assumptions, a RAID 3 disk array is considerably more costly than an equivalent RAID 5 array where both have equal capacity and throughput in a fully operational state. We assume that systems will be designed to meet (or slightly exceed) customer demand when they are fully operational. It is true that disk arrays could be designed to meet total customer demand in a failed mode, but given that failures are rare (as we show later) this would result in considerable waste of resources and a much higher system cost, for only a slight increase in revenue earned. It is, however, important to consider system reliability when comparing the two systems, and this is the focus of the next section.

4.5 Performability of RAID 3 vs RAID 5

In this section we conduct a performability analysis [Beau78] [Meye80] of both RAID 3 and RAID 5 disk arrays. The advantage of such an analysis over the more traditional reliability analysis is that it allows us to model both performance and reliability related events in combination. Performability analysis is formally introduced in [Meye80] and separately in [Beau78]. For more recent work in the field and excellent general treatment of the area refer to [Triv94] and [Smit88]. The only performability analysis of disk arrays that we have found is by Islam in [Isla93]. [Isla93], however, does not model the detailed reward model presented here and assumes identical repair times for single disk and full system failures. Also the results are not based on a particular disk array architecture and so do not accurately model any particular RAID scheme. We do, however, fol-

low a similar approach to that used in [Isla93] in the following analysis.

The operating states of both RAID arrays can be easily enumerated as 0, 1 and 2, where state 0 corresponds to no disks failed, state 1 to one disk failed and state 2 to a total system failure (2 or more disks failed). Although only three, this is a sufficient number of states to model the possible operational modes of a simple D+1 RAID array. (The D+1 notation simply refers to the fact that both RAID structures have D disks for data and 1 redundant disk for parity information independent of D)[7]. We next consider the performance of the system in each state and use this to define a reward structure which can be used in conjunction with a Markov Chain reliability analysis to gain a measure of performability.

4.5.1 Performance of Disk Arrays

Much work has been done in analysing the performance of RAID arrays in various modes of operation [Chen94b] [Munt90]. It is, however, important to consider the application for which the RAID is being utilised when interpreting the results of such work. Particularly, in the case of a video server we are dealing with a strictly read-only environment. Much of the performance degradation of RAID systems occurs during write or modify operations. Such operations will not happen in the normal operation of a video server. Only when a movie is initially loaded onto an array are writes taking place, and we assume this can be scheduled to occur during a lightly loaded time for the server. As such it is in a read-only environment that we consider the performance of RAID 3 and RAID 5 below.

4.5.1.1 RAID 3

Figure 4.5 illustrates the operation of a RAID 3 disk array composed of 3 data disks and 1 redundant disk before and after a single disk

7. In RAID 5 the parity blocks are actually distributed across all disks in the array, but the requirement is for one additional disk.

failure. Before the failure (in state 0) all three data disks are being accessed in parallel to service three separate requests. During this mode of operation, the parity disk is idle and so it's bandwidth is wasted. From Figure 4.5 this appears to be a large inefficiency, but as disk arrays get larger this inefficiency decreases. At some time, one of the data disks fails and the array enters a failure mode of operation (state 1). We see from Figure 4.5 that operation is almost exactly the same except that now some calculation is required by the array controller to correctly rebuild the data based on the parity information stored on the parity disk. The important aspect of the RAID 3 architecture is that it does not degrade at all after a single disk failure (that is, it is still able to support the same load as before the failure). It is for this reason that RAID 3 has been proposed in the literature for use in video storage [Chan95][Cohe95].

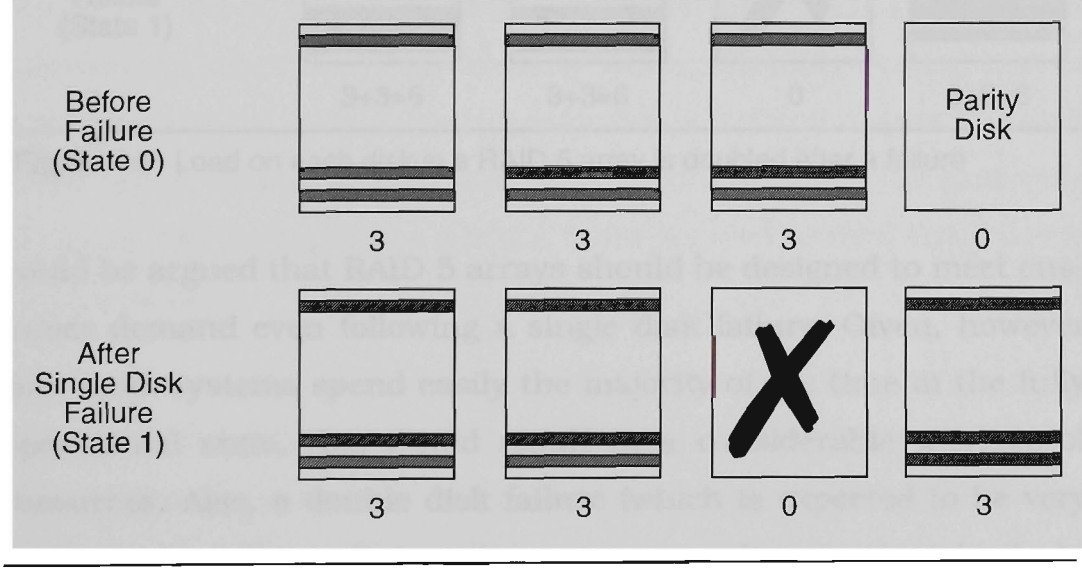


Figure 4.5 RAID 3 maintains throughput after a single failure

4.5.1.2 RAID 5

Figure 4.6 depicts the operation of a RAID 5 disk array before and after a failure. Since parity is distributed across all disks, we are effectively able to utilise all disks to read useful data before failure. Notice in the diagram that all four disks are serving three requests each (not simultaneously, but in a particular service round) before a failure occurs. After a failure, in order to recover the data on the

failed disk, all the other disks read the corresponding block and a parity calculation must be performed to determine the lost data. (These reads are shown by darker blocks in the figure)[8]. Note that the load on each disk is doubled following a disk failure. In a lightly loaded system this may be tolerable. However, in a highly utilised system (which is likely to be desirable given the cost) load will clearly need to be shed in the event of a disk failure. In light of this fact, it

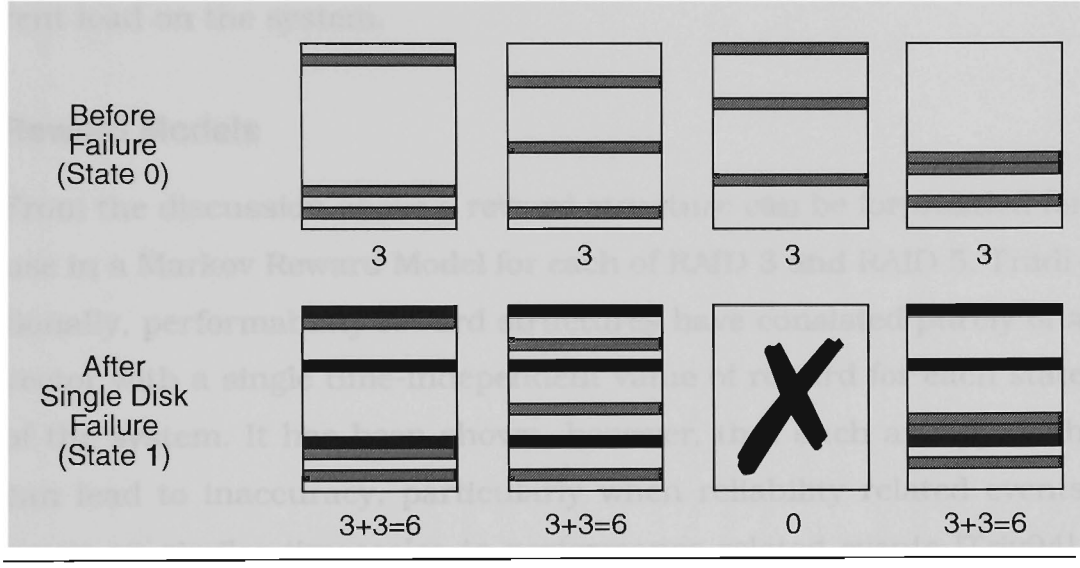


Figure 4.6 Load on each disk in a RAID 5 array is doubled after a failure

could be argued that RAID 5 arrays should be designed to meet customer demand even following a single disk failure. Given, however that most systems spend easily the majority of the time in the fully operational state, this would result in a considerable wastage of resources. Also, a double disk failure (which is expected to be very rare) would still result in either system needing to shed load. As such, we maintain the assumption that both RAID 3 and RAID 5 systems are designed for the same throughput and capacity when fully operational.

From Section 4.4.1 it is known that RAID 5 architectures perform more efficiently in a fully operational state (obtaining the same throughput as a RAID 3 with considerably fewer disks) but it is now

8. An alternative suggested by [Mour96] is to wait until these blocks are read in the following service rounds, but this will increase both buffering and admission delay by a factor of D.

clear that RAID 5 degrades significantly (needing to shed up to 50% of load) following a single disk failure. RAID 3 architectures are not as efficient during normal operation, but are able to maintain performance following a single disk failure. Neither RAID architecture can survive multiple disk failures without an intervening repair. Given this trade-off between the two techniques we are able to assign reward values to each array based on its state and the current load on the system.

4.5.1.3 Reward Models

From the discussion above a reward structure can be formulated for use in a Markov Reward Model for each of RAID 3 and RAID 5. Traditionally, performability reward structures have consisted purely of a vector with a single time-independent value of reward for each state of the system. It has been shown, however, that such an approach can lead to inaccuracy, particularly when reliability related events occur on similar timescales to performance related events [Triv94]. Since repair times and load fluctuations both occur on the timescale of hours (although failures don't) a more detailed reward structure is employed here.

The potential for an interactive video server to earn revenue (ie. reward) varies greatly with time of day. In a typical VOD server, peak time might occur at 8pm, with (say) 1000 viewers. But at 5am the number of viewers might only be 50. Clearly it is more important that the disk array be fully operational during peak times. In order to account for this variation we introduce a discrete-time time-dependent reward structure. This implies that the reward structure is now a matrix of values dependent both on the state of the system and the time-of-day. By using data from television ratings we develop a profile of viewer load versus time of day (Figure 4.7). Although this profile may not identically match the future profile of interactive video services, the trends are likely to be similar. Importantly, the analysis presented here is independent of this viewer pro-

file and as such a more appropriate profile can be readily inserted if such were available. Note that the data shown is only available as discrete values (generally in hourly intervals) hence the motivation for using a discrete-time reward structure. We see from Figure 4.7

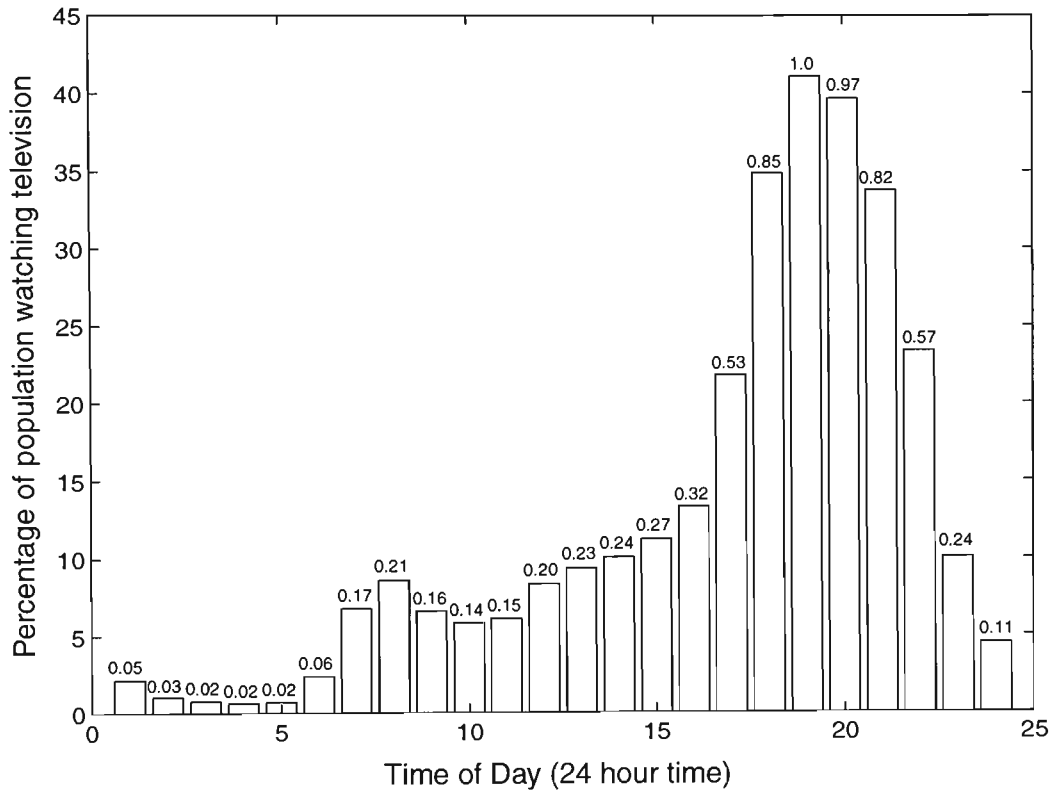


Figure 4.7 Viewers vs Time of Day (source A. C. Neilsen - Australian TV ratings)

that the peak load is considerably higher than the mean and as such the time that a disk array fails and the time to repair will have a considerable effect on reward earned. The numbers shown on top of each bar represent the load on the server at that time of day, normalised such that the peak load represents one unit.

Consider the case where a disk array has been designed to be 100% utilised under peak load when it is fully operational (ie. in State 0). If RAID 5 is used and a disk fails during peak hour we must drop to 50% of the offered load, with RAID 3 such a reduction is not necessary. If two disks fail, however, both systems will drop the entire load until a repair can be affected. The reward structures used for RAID 3 (Re_3) and RAID 5 (Re_5) are shown in Equation 4.21 and

Equation 4.22 and correspond to the viewer versus time of day profile shown in Figure 4.7. Notice that the number of rows in the reward structure corresponds to the 3 possible states of the system, while each of the 24 columns correspond to a one hour time slot during the day. Neither of the reward structures shown account for increased load during a repair operation or the potential of lost revenue due to customer dissatisfaction during a failure period. It is straightforward to alter the reward structure to incorporate such aspects, but the precise value of the change is more difficult to determine.

RAID 3:

$$Re_3 = \begin{bmatrix} 0.05 & 0.03 & 0.02 & 0.02 & 0.02 & 0.06 & 0.17 & 0.21 & 0.16 & 0.14 & 0.15 & 0.20 \\ 0.05 & 0.03 & 0.02 & 0.02 & 0.02 & 0.06 & 0.17 & 0.21 & 0.16 & 0.14 & 0.15 & 0.20 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.23 & 0.24 & 0.27 & 0.32 & 0.53 & 0.85 & 1.0 & 0.97 & 0.82 & 0.57 & 0.24 & 0.11 \\ 0.23 & 0.24 & 0.27 & 0.32 & 0.53 & 0.85 & 1.0 & 0.97 & 0.82 & 0.57 & 0.24 & 0.11 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad \text{(Eqn 4.21)}$$

The shaded section of the reward structure in each case shows where they differ. In the case of RAID 3, even with a failed disk the full load is still supported, whereas with RAID 5 the maximum load supported with a single failed disk is 0.5.

RAID 5:

$$Re_5 = \begin{bmatrix} 0.05 & 0.03 & 0.02 & 0.02 & 0.02 & 0.06 & 0.17 & 0.21 & 0.16 & 0.14 & 0.15 & 0.20 \\ 0.05 & 0.03 & 0.02 & 0.02 & 0.02 & 0.06 & 0.17 & 0.21 & 0.16 & 0.14 & 0.15 & 0.20 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.23 & 0.24 & 0.27 & 0.32 & 0.53 & 0.85 & 1.0 & 0.97 & 0.82 & 0.57 & 0.24 & 0.11 \\ 0.23 & 0.24 & 0.27 & 0.32 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.5 & 0.24 & 0.11 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad \text{(Eqn 4.22)}$$

With a detailed reward structure in place the next section considers the development and solution of a Markov Chain analysis for the reliability of each array. Note that both RAID 3 and RAID 5 have the same reliability model (they are both D+1 arrays), it is the reward models (ie. performance in different states) that differ, as shown in Equation 4.21 and Equation 4.22.

4.5.2 Reliability of D+1 Disk Arrays

In this section we present a Continuous Time Markov Chain analysis of disk arrays with one redundant disk. This analysis is an extension of that found in [Ng89] in that it accounts for the repair time in the case of a total system failure. In other words the state of two disks failed (state 2 in Figure 4.8) is not an absorbing state. Consider the Markov Chain representation shown in Figure 4.8.

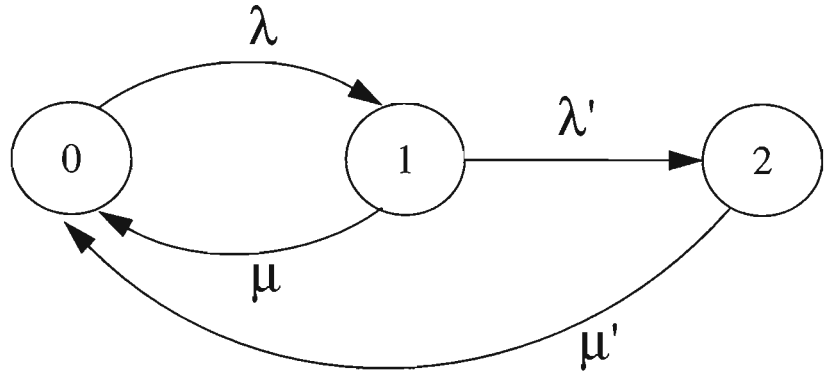


Figure 4.8 Markov Chain for array reliability

For a disk array with D disks, we note that:

$$\begin{aligned}
\lambda_s &= \text{Failure Rate of a Single Disk} = 1/\text{MTTF} \\
\lambda' &= (D-1)\lambda_s \\
\lambda &= D\lambda_s \\
\mu &= \text{Rebuild Rate after Single Failure} = 1/\text{MTTR(1)} \\
\mu' &= \text{Repair Rate after Total Failure} = 1/\text{MTTR(F)}
\end{aligned} \qquad \text{(Eqn 4.23)}$$

Note that μ and μ' represent the rebuild rate of a single disk and the repair rate of the entire array respectively. It is likely that the rebuild after a single disk failure will be automated (using hot-spares) and will not require human intervention. The repair of a total system failure, however, is a much larger task requiring the reloading of the entire array, and will probably require human intervention. As such it is assumed that $\mu \geq \mu'$.

Now define the state transition matrix between each of the states as shown below:

$$\begin{array}{cc} & \text{Next State} \\ & \begin{array}{ccc} s_0 & s_1 & s_2 \end{array} \\ \text{Present State} \begin{array}{c} s_0 \\ s_1 \\ s_2 \end{array} & \begin{bmatrix} 1-\lambda\Delta t & \lambda\Delta t & 0 \\ \mu\Delta t & 1-\mu\Delta t-\lambda'\Delta t & \lambda'\Delta t \\ \mu'\Delta t & 0 & 1-\mu'\Delta t \end{bmatrix} \end{array} \qquad \text{(Eqn 4.24)}$$

From the transition matrix shown in Equation 4.24, individual state transition probabilities are obtained and rearranged to give:

$$\begin{aligned} \frac{P_0(t+\Delta t)-P_0(t)}{\Delta t} &= -\lambda P_0(t)+\mu P_1(t)+\mu' P_2(t) \\ \frac{P_1(t+\Delta t)-P_1(t)}{\Delta t} &= \lambda P_0(t)-(\mu+\lambda')P_1(t) \\ \frac{P_2(t+\Delta t)-P_2(t)}{\Delta t} &= \lambda' P_1(t)-\mu' P_2(t) \end{aligned} \qquad \text{(Eqn 4.25)}$$

Taking the limit as $\Delta t \to 0$:

$$\begin{aligned} \dot{P}_0(t)+\lambda P_0(t)-\mu P_1(t)-\mu' P_2(t) &= 0 \\ \dot{P}_1(t)+(\mu+\lambda')P_1(t)-\lambda P_0(t) &= 0 \\ \dot{P}_2(t)+\mu' P_2(t)-\lambda' P_1(t) &= 0 \end{aligned} \qquad \text{(Eqn 4.26)}$$

Determining Laplace transforms of the above differential equations:

$$\begin{aligned} sP_0(s)-P_0(0)+\lambda P_0(s)-\mu P_1(s)-\mu' P_2(s) &= 0 \\ sP_1(s)-P_1(0)+(\mu+\lambda')P_1(s)-\lambda P_0(s) &= 0 \\ sP_2(s)-P_2(0)+\mu' P_2(s)-\lambda' P_1(s) &= 0 \end{aligned} \qquad \text{(Eqn 4.27)}$$

At time 0 the array is fully functional and as such $P_0(0) = 1$, and $P_1(0) = P_2(0) = 0$. This gives the following set of linear equations in the s domain:

$$\begin{bmatrix} s+\lambda & -\mu & -\mu' \\ -\lambda & s+\mu+\lambda' & 0 \\ 0 & -\lambda' & s+\mu' \end{bmatrix} \begin{bmatrix} P_0(s) \\ P_1(s) \\ P_2(s) \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \qquad \text{(Eqn 4.28)}$$

Solving using Cramer's Rule we obtain:

$$\begin{aligned} P_0(s) &= (s^2+s(\mu'+\mu+\lambda')+\mu'(\mu+\lambda'))/d \\ P_1(s) &= (s+\mu')\lambda/d \\ P_2(s) &= \lambda\lambda'/d \end{aligned} \qquad \text{(Eqn 4.29)}$$

where $d = s(s^2+s(\mu'+\mu+\lambda'+\lambda)+\mu\mu'+\lambda\lambda'+\lambda'\mu'+\lambda\mu')$

Next expand each of $P_0(s)$, $P_1(s)$, $P_2(s)$, into partial fractions to allow us to take the inverse Laplace Transform. First, rewrite d as follows:

$$\begin{aligned} d &= s(s^2 + s(\mu' + \mu + \lambda' + \lambda) + \mu\mu' + \lambda\lambda' + \lambda'\mu' + \lambda\mu') \\ &= s(s - r_1)(s - r_2) \end{aligned} \qquad \text{(Eqn 4.30)}$$

$$\text{where } r_1, r_2 = \frac{-(\mu' + \mu + \lambda' + \lambda) \pm \sqrt{(\mu' + \mu + \lambda' + \lambda)^2 - 4(\mu\mu' + \lambda\lambda' + \lambda'\mu' + \lambda\mu')}}{2}$$

Now, for $P_0(s)$:

$$\begin{aligned} P_0(s) &= \frac{s^2 + s(\mu' + \mu + \lambda') + \mu'(\mu + \lambda')}{s(s - r_1)(s - r_2)} \\ &= \frac{a_0}{s} + \frac{b_0}{s - r_1} + \frac{c_0}{s - r_2} \\ &= \frac{a_0(s^2 - s(r_1 + r_2) + r_1 r_2) + b_0(s^2 - sr_2) + c_0(s^2 - sr_1)}{s(s - r_1)(s - r_2)} \\ &= \frac{(a_0 + b_0 + c_0)s^2 + (-a_0(r_1 + r_2) - b_0 r_2 - c_0 r_1)s + a_0 r_1 r_2}{s(s - r_1)(s - r_2)} \end{aligned} \qquad \text{(Eqn 4.31)}$$

which implies:

$$\begin{aligned} a_0 + b_0 + c_0 &= 1 \\ -a_0 r_1 - a_0 r_2 - b_0 r_2 - c_0 r_1 &= \mu' + \mu + \lambda' \\ a_0 r_1 r_2 &= \mu'(\mu + \lambda') \end{aligned} \qquad \text{(Eqn 4.32)}$$

and solving for a_0, b_0, c_0 gives:

$$\begin{aligned} a_0 &= \frac{\mu'(\mu + \lambda')}{r_1 r_2} \\ b_0 &= \frac{r_1\mu + r_1\lambda' + r_1^2 + r_1\mu' + \mu\mu' + \lambda'\mu'}{r_1(r_1 - r_2)} \\ c_0 &= -\frac{r_2\mu + r_2\lambda' + r_2^2 + r_2\mu' + \mu\mu' + \lambda'\mu'}{r_2(r_1 - r_2)} \end{aligned} \qquad \text{(Eqn 4.33)}$$

$$\text{and } P_0(s) = \frac{a_0}{s} + \frac{b_0}{s - r_1} + \frac{c_0}{s - r_2}$$

Expanding similarly for $P_1(s)$ and $P_2(s)$ we obtain:

$$
\begin{aligned}
a_1 &= \frac{\mu'\lambda}{r_1 r_2} \\
b_1 &= \frac{\lambda(r_1+\mu')}{r_1(r_1-r_2)} \\
c_1 &= -\frac{\lambda(\mu'+r_2)}{r_2(r_1-r_2)} \\
\text{and } P_1(s) &= \frac{a_1}{s} + \frac{b_1}{s-r_1} + \frac{c_1}{s-r_2}
\end{aligned}
\qquad \text{(Eqn 4.34)}
$$

and

$$
\begin{aligned}
a_2 &= \frac{\lambda\lambda'}{r_1 r_2} \\
b_2 &= \frac{\lambda\lambda'}{r_1(r_1-r_2)} \\
c_2 &= -\frac{\lambda\lambda'}{r_2(r_1-r_2)} \\
\text{and } P_2(s) &= \frac{a_2}{s} + \frac{b_2}{s-r_1} + \frac{c_2}{s-r_2}
\end{aligned}
\qquad \text{(Eqn 4.35)}
$$

Notice from Equation 4.29 that:

$$
\begin{aligned}
P_0(s) + P_1(s) + P_2(s) &= \frac{1}{s} \\
\text{which implies } P_0(t) + P_1(t) + P_2(t) &= 1 \qquad \forall t \geq 0
\end{aligned}
\qquad \text{(Eqn 4.36)}
$$

implying that the sum of the probabilities of state is always unity, which is a necessary condition.

Finally take the inverse Laplace transforms in a straightforward manner to obtain:

$$
\begin{aligned}
P_0(t) &= a_0 + b_0 e^{r_1 t} + c_0 e^{r_2 t} \\
P_1(t) &= a_1 + b_1 e^{r_1 t} + c_1 e^{r_2 t} \\
P_2(t) &= a_2 + b_2 e^{r_1 t} + c_2 e^{r_2 t}
\end{aligned}
\qquad \text{(Eqn 4.37)}
$$

and we have the complete solution. We can further show that r_1 and r_2 are always real and negative (see below) and as such in steady state (ie. as $t \to \infty$) the probabilities of state become:

$$P_0 = a_0 = \frac{\mu'(\mu+\lambda')}{r_1 r_2} = \frac{\mu'(\mu+\lambda')}{\mu\mu'+\lambda\lambda'+\lambda'\mu'+\lambda\mu'}$$
$$P_1 = a_1 = \frac{\mu'\lambda}{r_1 r_2} = \frac{\mu'\lambda}{\mu\mu'+\lambda\lambda'+\lambda'\mu'+\lambda\mu'} \quad \text{(Eqn 4.38)}$$
$$P_2 = a_2 = \frac{\lambda\lambda'}{r_1 r_2} = \frac{\lambda\lambda'}{\mu\mu'+\lambda\lambda'+\lambda'\mu'+\lambda\mu'}$$

Now consider r_1 and r_2 from Equation 4.30, which is reproduced here:

$$r_1, r_2 = \frac{-(\mu'+\mu+\lambda'+\lambda) \pm \sqrt{(\mu'+\mu+\lambda'+\lambda)^2 - 4(\mu\mu'+\lambda\lambda'+\lambda'\mu'+\lambda\mu')}}{2} \quad \text{(Eqn 4.39)}$$

Consider the term under the radical:

$$\begin{aligned}&(\mu'+\mu+\lambda'+\lambda)^2 - 4(\mu\mu'+\lambda\lambda'+\lambda'\mu'+\lambda\mu') \quad \text{(Eqn 4.40)}\\ &= \mu'^2+\mu\mu'+\mu'\lambda'+\mu'\lambda+\mu\mu'+\mu^2+\mu\lambda'+\mu\lambda+\lambda'\mu'\\ &+\lambda'^2+\lambda\lambda'+\lambda\mu'+\lambda\mu+\lambda\lambda'+\lambda^2-4\mu\mu'-4\lambda\lambda'-4\lambda'\mu'-4\lambda\mu'\\ &= \mu'^2+\mu^2+\lambda'^2+\lambda^2-2\mu\mu'-2\mu'\lambda'-2\lambda\lambda'-2\lambda\mu'+2\mu\lambda'+2\mu\lambda\\ &= (\mu-\mu')^2+(\lambda-\lambda')^2+2(\lambda+\lambda')(\mu-\mu')\end{aligned}$$

Assuming that $\mu \geq \mu'$, which simply implies that a multiple disk failure will take at least as long to repair as a single disk failure, then we can see that the term under the radical is always positive and as such r_1 and r_2 are always real.

Now, to show that both r_1 and r_2 are always negative we need:

$$(\mu'+\mu+\lambda'+\lambda) > \sqrt{(\mu'+\mu+\lambda'+\lambda)^2 - 4(\mu\mu'+\lambda\lambda'+\lambda'\mu'+\lambda\mu')} \quad \text{(Eqn 4.41)}$$

Squaring both sides we get:

$$(\mu'+\mu+\lambda'+\lambda)^2 > (\mu'+\mu+\lambda'+\lambda)^2 - 4(\mu\mu'+\lambda\lambda'+\lambda'\mu'+\lambda\mu') \quad \text{(Eqn 4.42)}$$

which gives:

$$0 > -4(\mu\mu'+\lambda\lambda'+\lambda'\mu'+\lambda\mu') \quad \text{(Eqn 4.43)}$$

which is always true since $\mu > 0, \mu' > 0, \lambda > 0, \lambda' > 0$.

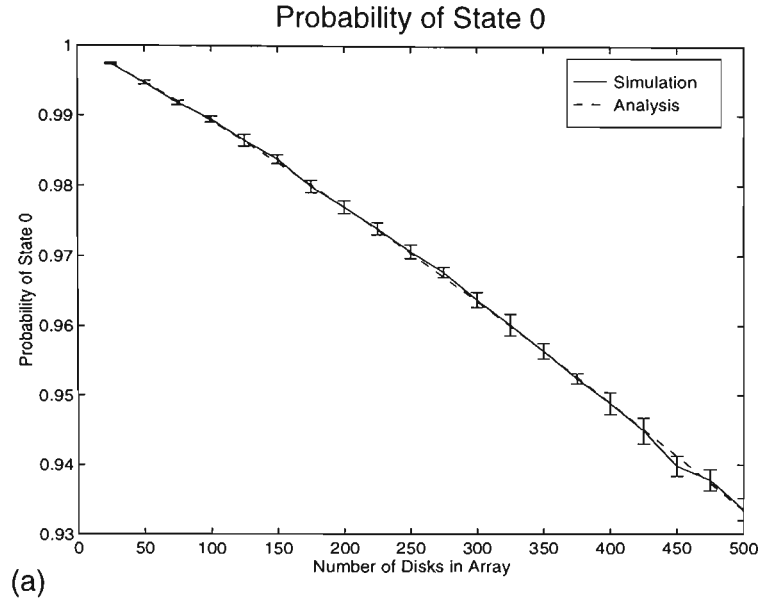
Hence, we see that both r_1 and r_2 are always real and negative, and as such the exponential terms in our solutions (Equation 4.37) are decaying with time. This fact leads to the steady-state solutions shown in Equation 4.38.

4.5.2.1 Validation of Reliability Model

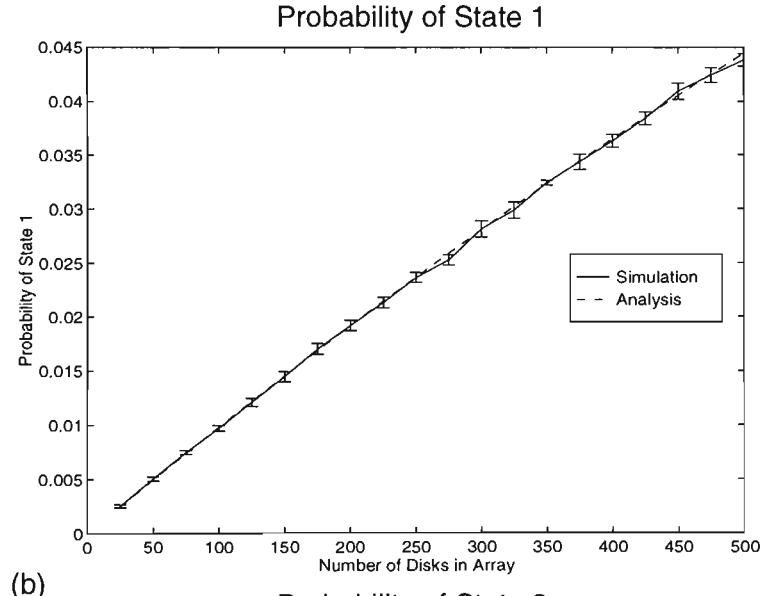
In order to validate and extend the Markov chain reliability model derived above, an event driven simulation has been used in order to relax some of the constraints made in the derivation of the model. Specifically, failure and repair times may not be exponentially distributed as was assumed by the Markov model of Figure 4.8.

Before modifying these assumptions, consider the event-driven simulation where failure and repair times are exponentially distributed. In this case the results for probability of state of the array should match exactly with the results derived in Equation 4.37. Figure 4.9 shows the equilibrium probabilities of state (for states 0, 1 and 2) versus the number of disks in the array. The MTTF of a single disk is assumed to be 10,000 days (240,000 hours) and the MTTR a single failure (denoted MTTR(1)) is 1 day (24 hours) and MTTR a total failure (denoted MTTR(F)) is 10 days (240 hours). Note that these MTTR assumptions are deliberately conservative; in reality shorter repair times would be expected. The results of the simulation and analysis are seen to be in total agreement over the full range of values shown here. Although not included here, extensive investigations of other sets of parameters reveal that this agreement is always maintained while the assumptions of exponentially distributed failure and repair times are applied.

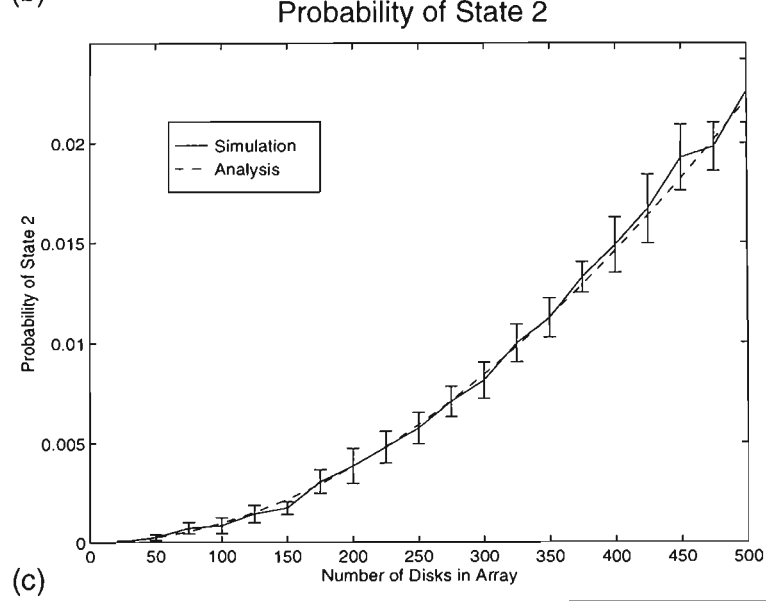
Of further interest is the robustness of the analysis to variation in the exponential assumptions made concerning failure and repair times. Specifically, it is unlikely that repair times will be exponentially distributed. It seems more likely that repair times would be deterministic or uniformly distributed over some time interval. Further, although detailed information regarding failure of disk drives is unavailable, other forms of mechanical failure are commonly modelled by a Weibull distribution [Shoo68]. The exponential reliability function assumed by the Markov model above, is based on the assumption that failures are equally likely to occur at all times. In



(a)



(b)



(c)

Figure 4.9 Probabilities of state obtained via simulation and analysis for states 0,1 and 2 respectively.

other words the hazard rate is constant. Actually, mechanical failures generally have a hazard rate which can be modelled by a "bathtub" curve as shown in Figure 4.10.

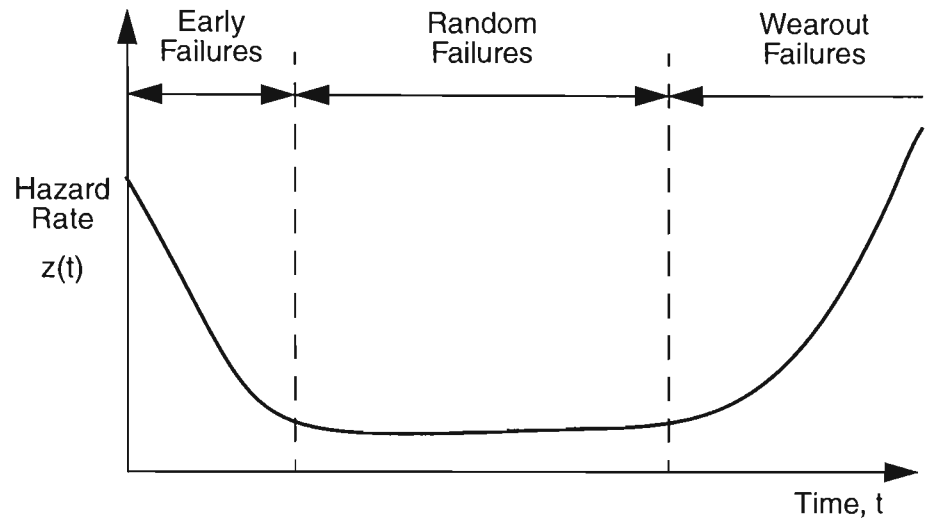


Figure 4.10 General form of mechanical failure curves (from [Shoo68])

According to this bathtub curve, failures are more likely soon after power on (early failures or infant mortality), and toward the end of a product's life (wearout failures). Between these two periods, failures are relatively unlikely and are termed random failures. The reliability function of a single device is obtained from this hazard function according to Equation 4.44

$$R(t) = \exp\left[-\int_0^t z(\xi)\,d\xi\right] \qquad \text{(Eqn 4.44)}$$

where z(t) is the hazard rate as a function of time, an example of which is shown in Figure 4.10. Equation 4.44 leads to the exponential reliability function for the case of the constant hazard function. In the case of the bathtub curve a mathematical model is considerably harder to derive. A piecewise linear model can be used, but a more common solution is to employ the Weibull distribution. The Weibull distribution is analytically tractable and can be used to model either early failures or wearout failure with the variation of a single parameter. The hazard curve of the Weibull model is given by:

$$z(t) = Kt^m \qquad \text{for } m > -1 \qquad \text{(Eqn 4.45)}$$

Which, from Equation 4.44 leads to the reliability function:

$$R(t) = \exp\left(\frac{-Kt^{m+1}}{m+1}\right) \qquad \text{(Eqn 4.46)}$$

Now, assuming that the MTTF of the drive is known, K can be fixed and m chosen to model the effects of either early failures or wearout failures. The MTTF of any device is readily calculated from the reliability function according to:

$$\text{MTTF} = \int_0^\infty R(t)dt \qquad \text{(Eqn 4.47)}$$

which, for the Weibull model gives:

$$\text{MTTF} = \frac{\Gamma[1/(m+1)]}{(m+1)[K/(m+1)]^{1/(m+1)}} \qquad \text{(Eqn 4.48)}$$

which, upon specification of MTTF, and m (the shape parameter) can be rearranged to give K which can then be used in Equation 4.46 to reveal the complete reliability model. It should be noted that when m=0 the Weibull model reduces to the exponential reliability model, and as $m \to \infty$ the model approaches a deterministic failure model where all devices fail at exactly the same time. Values of m between -1 and 0 model infant mortality, while values greater than 0 model wearout failures.

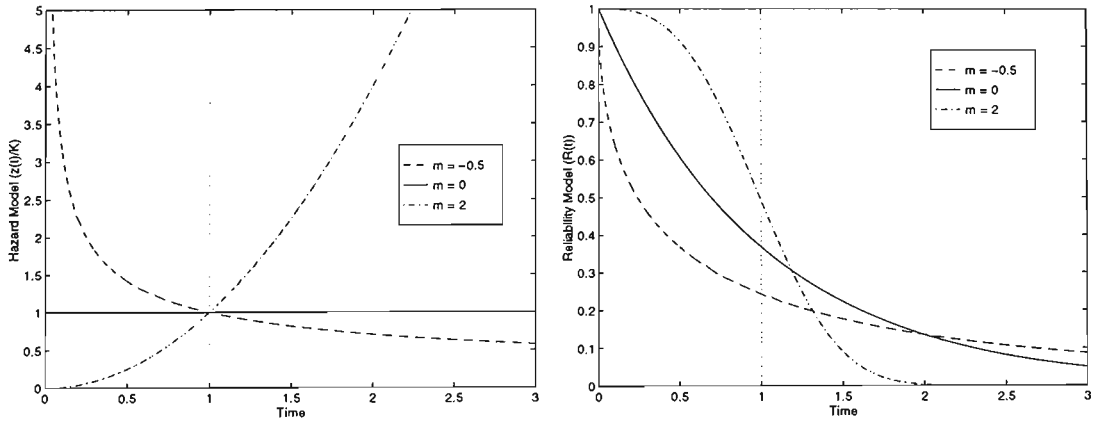


Figure 4.11 Hazard and reliability curves of the Weibull model.

The curves in Figure 4.11 show hazard functions and corresponding reliability models for various values of m. The dotted vertical line represents the MTTF of all curves which has been normalised to unity. The curves confirm the fact that a negative value of m leads to high infant mortality while a higher positive value increases the likelihood of wearout failure.

The more flexible failure and repair models shown in Figure 4.11 are easily incorporated into the simulation model which has already been validated against the analysis of Section 4.5.2. Figure 4.12 illustrates the effect of variations in these distributions on the overall reliability of the system.

Figure 4.12 shows the probabilities of state for a range of Weibull shape parameters (m) and three different repair time distributions. All repair time distributions have a mean of 1 day for a single failure and 10 days for a total failure. The uniform case ranges from 0 to 2 for a single repair and 0 to 20 days for a full repair. The exponential case merely reverts to the base assumption of exponentially distributed service times with the appropriate mean, while the deterministic case fixes the service time at the mean for every repair. The Weibull shape parameter for the failure distribution was varied from -0.5, corresponding to a high rate of early failures, to 10 which results in an almost deterministic time to fail located at the mean. For the curves shown, 100 disks per array were assumed, with an individual MTTF of 10,000 days.

From Figure 4.12 it is observed that a high early failure rate leads to a slight decrease in availability. This is despite the fact that the MTTF is the same as the other cases. This can be explained by the large number of disks in the array. With such a large number, some early failures are very likely and the corresponding delay incurred while waiting for repair leads to a lower overall availability. As m is increased, an improvement in reliability is witnessed, which remains until the value of m causes the Weibull distribution to approach a

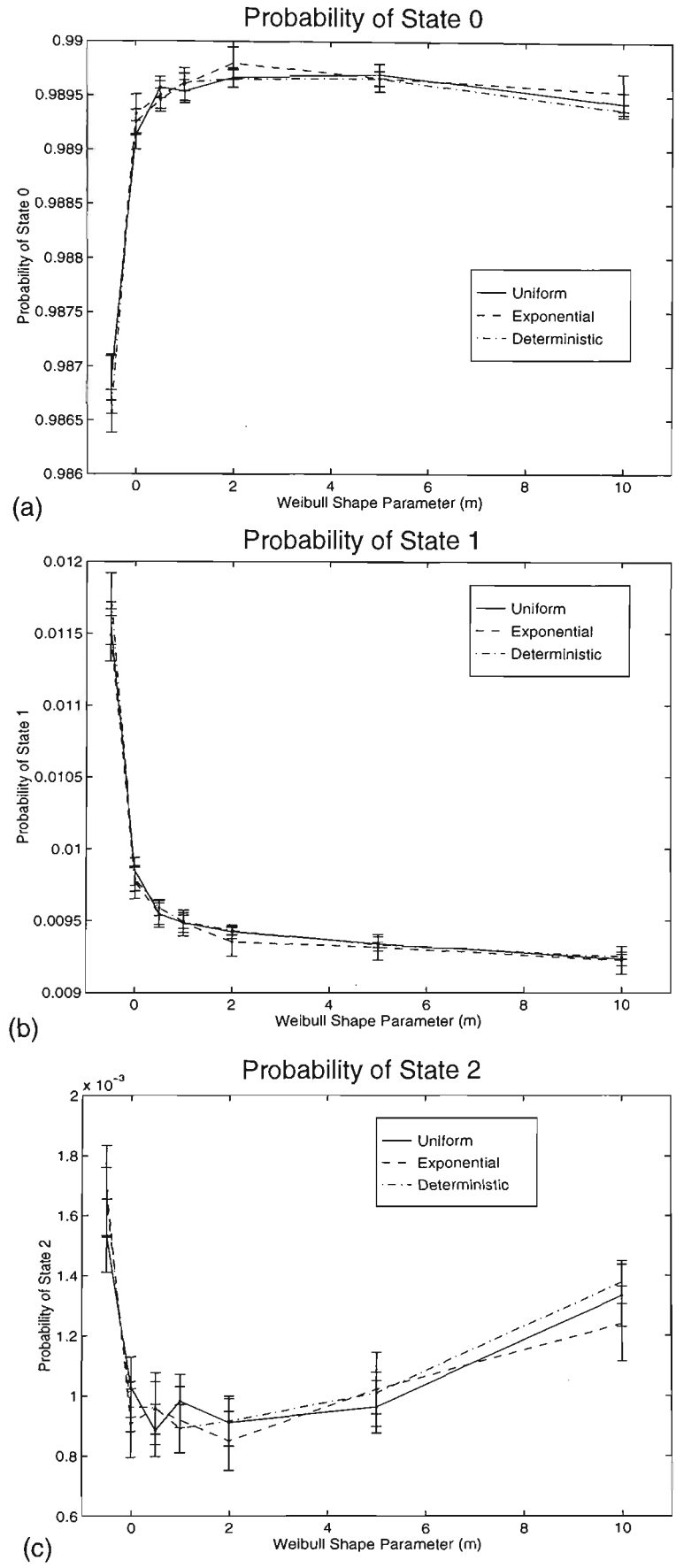


Figure 4.12 Probabilities of state for a range of Weibull distributions of failure time and three repair time distributions

deterministic distribution at the mean. At this point, all disks are likely to fail at exactly the same time. For this reason an increase in the probability of double disk failures is observed while the probability of single disk failures remains monotonically decreasing. The effect of more double disk failures is to decrease overall system availability (as evidenced by P_0) due to the longer repair time incurred in this case.

Regarding repair times, the graphs of Figure 4.12 reveal that the distribution of the repair times has no significant effect on the probabilities of state of the system. This is explained by the infrequency of these repair events. Provided the mean repair times are equal, actual distributions are unimportant. In general, the effect of varying either the failure or repair distributions has only a marginal effect on the probabilities of state determined by simulation. When it is considered that early failures are unlikely in modern disk drives due to appropriate quality control measures and burn in tests, this statement is further reinforced.

Figure 4.13 shows the probabilities of state versus the MTTF of an individual disk for several repair time scenarios. The lines shown are the analytical results, while the error bars represent the corresponding simulation with uniformly distributed repair times (from zero to double the mean) and a Weibull shape parameter of 2 for the failure distribution. (Note that the horizontal scale is magnified in Figure 4.13 (c).) The first observation is that once again the simulation and analytical results are in excellent agreement.

Figure 4.13 reveals that single disk repair time (MTTR(1) measured in days, which is the first figure in the legend in each case) has a greater effect on overall system reliability, than full system repair time (MTTR(F), in days, the second figure in the legend). That is, while ever the single repair time is low, the probability of the system operating in state 0 is considerably higher. This is most readily observed in the difference between the solid line and the dashed and

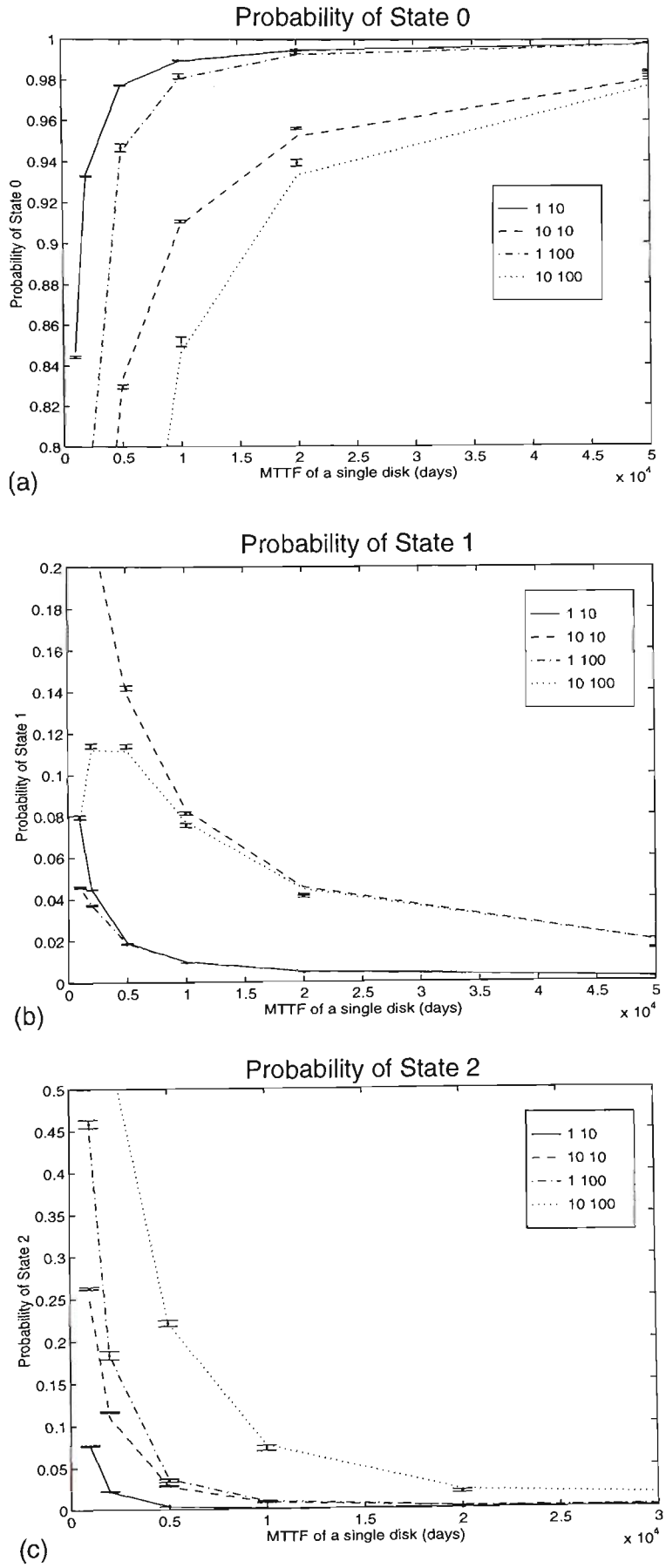


Figure 4.13 Probabilities of state for a range of disk MTTF's and MTTR's (the first figure in the legend represents MTTR(1) the second is MTTR(F) both measured in days).

chain lines of Figure 4.13 (a). Increasing the total repair time by a factor of 10 (the chain line) has only a small effect, while an equivalent increase in the single repair time has a considerable effect on system reliability, as evidenced by the dashed line. Of course increasing both results in the least reliable system as shown by the dotted line. This result is not unexpected since single failure are far more common than multiple failures, hence the importance of the single-disk rebuild time, in determining overall system reliability.

The other results are largely as expected apart perhaps from the dotted line of Figure 4.13 (b). At low disk reliabilities the long repair times result in the system spending the majority of the time in state 2. As MTTF is increased however, this probability reduces rapidly, while the probability of state 1 increases. Further increases in disk reliability, however cause the probability of state 0 to rise, resulting in falling probabilities of both states 1 and 2. This set of events causes the humped appearance observed in the figure. Note that a similar hump would occur for all the graphs if disk reliability was lowered far enough.

From this validation of the Markov Model discussed above, several conclusions can be drawn. First, the analytic results are in total agreement with simulation results under identical (Markovian) assumptions. Further, as assumptions regarding failure distributions and repair distributions are relaxed in the simulation, overall probabilities of state are not greatly affected (see Figure 4.12). The only significant effect is the reduction of reliability when infant mortalities are high, which is unlikely in modern magnetic drives. This result implies that the results of the analysis used above are quite robust even for non-exponential distributions of failure and repair times. Having validated the usefulness of the analytic results of Equation 4.38 the next section incorporates these results into a performability analysis in order to gain an overall figure of merit for RAID 3 and RAID 5 disk arrays.

4.5.3 Performability

The performance and reliability models can now be integrated to gain insight into the expected revenue earned over a fixed period of time. The standard measure of performability is the amount of reward earned over a given mission time, and it is the expectation of this quantity that is derived here. We denote the reward rate of a system at time t and in state i by $r_{i,t \bmod p}$ where p is the period of our reward structure (in Equation 4.21 and Equation 4.22, 24 hours). If Z(t) is the state of the system at time t where $Z(t) \in \{0, 1, 2\}$ then we define X(t) as the reward rate of the system at time t. That is, $X(t) = r_{Z(t),\, t \bmod p}$. Now let Y(t) be the accumulated reward at time t. Clearly,

$$Y(t) = \int_0^t X(\tau)d\tau \qquad \text{(Eqn 4.49)}$$

In order to gain the expectation of Y(t) we use the following:

$$\begin{aligned} E[Y(t)] &= E\left[\int_0^t X(\tau)d\tau\right] \\ &= \int_0^t E[X(\tau)]d\tau \end{aligned} \qquad \text{(Eqn 4.50)}$$

Now, E[X(t)] can be found from:

$$E[X(t)] = \sum_{i=0}^{2} r_{i,\, t \bmod p} P_i(t) \qquad \text{(Eqn 4.51)}$$

Therefore,

$$E[Y(t)] = \int_0^t \left\{ \sum_{i=0}^{2} r_{i,\, \tau \bmod p} P_i(\tau) \right\} d\tau \qquad \text{(Eqn 4.52)}$$

In order to remove the r term from the integral we divide the integral into time units Δt over which r is constant (due to the discrete nature of the reward process) and set $n = t/(\Delta t)$, to be the number of such intervals from 0 to t. We then add a summation to total the reward earned over each Δt. Thus,

$$E[Y(t)] = \sum_{w=0}^{n} \left\{ \sum_{i=0}^{2} r_{i,\, t_w \bmod p} \left[\int_{t_w}^{t_w+\Delta t} P_i(\tau)\, d\tau \right] \right\} \qquad \text{(Eqn 4.53)}$$

Evaluating the integral from Equation 4.53 using Equation 4.37:

$$E[Y(t)] = \sum_{w=0}^{n} \left\{ \sum_{i=0}^{2} r_{i,\, t_w \bmod p} \left[a_i \Delta t + \frac{b_i}{r_1}(\exp(r_1(t_w+\Delta t)) - \exp(r_1 t_w)) + \frac{c_i}{r_2}(\exp(r_2(t_w+\Delta t)) - \exp(r_2 t_w)) \right] \right\} \qquad \text{(Eqn 4.54)}$$

which provides the exact expectation of reward over a mission time t for a system starting from a fully operational state (state 0). If mission time is very long, the equilibrium probabilities of state (Equation 4.38) can be used in place of the transient probabilities of Equation 4.37. This results in the following steady-state expectation of Y(t):

$$\begin{aligned} E[Y(t)] &= \sum_{w=0}^{n} \left\{ \sum_{i=0}^{2} r_{i,\, t_w \bmod p} a_i \Delta t \right\} \\ &= \sum_{i=0}^{2} \left\{ \sum_{w=0}^{n} r_{i,\, t_w \bmod p} a_i \Delta t \right\} \\ &= \sum_{i=0}^{2} a_i \sum_{w=0}^{n} r_{i,\, t_w \bmod p} \Delta t \\ &= \sum_{i=0}^{2} a_i t \sum_{w=0}^{n} \frac{r_{i,\, t_w \bmod p}}{n} \\ &= \sum_{i=0}^{2} a_i \bar{r}_i t \end{aligned} \qquad \text{(Eqn 4.55)}$$

Note that the distribution of Y(t) can also be obtained, but this is considerably more effort [Smit88] and expectations are sufficient for the exposition present here.

Equation 4.54 (or Equation 4.55) allows determination of the expected reward earned by either RAID 3 or RAID 5 over a certain mission time given that the system starts in a fully operational state. This "reward" can be directly related to the revenue earned by a video server in the same time by multiplying by a constant of propor-

tionality which represents the charge made for each hour of video. As an example, consider RAID 3 and RAID 5 disk arrays, both consisting of an equal number of disks (which implies that they do NOT have equal throughput). The performability of each array is shown in Figure 4.14. This graph shows the expected result, that performabil-

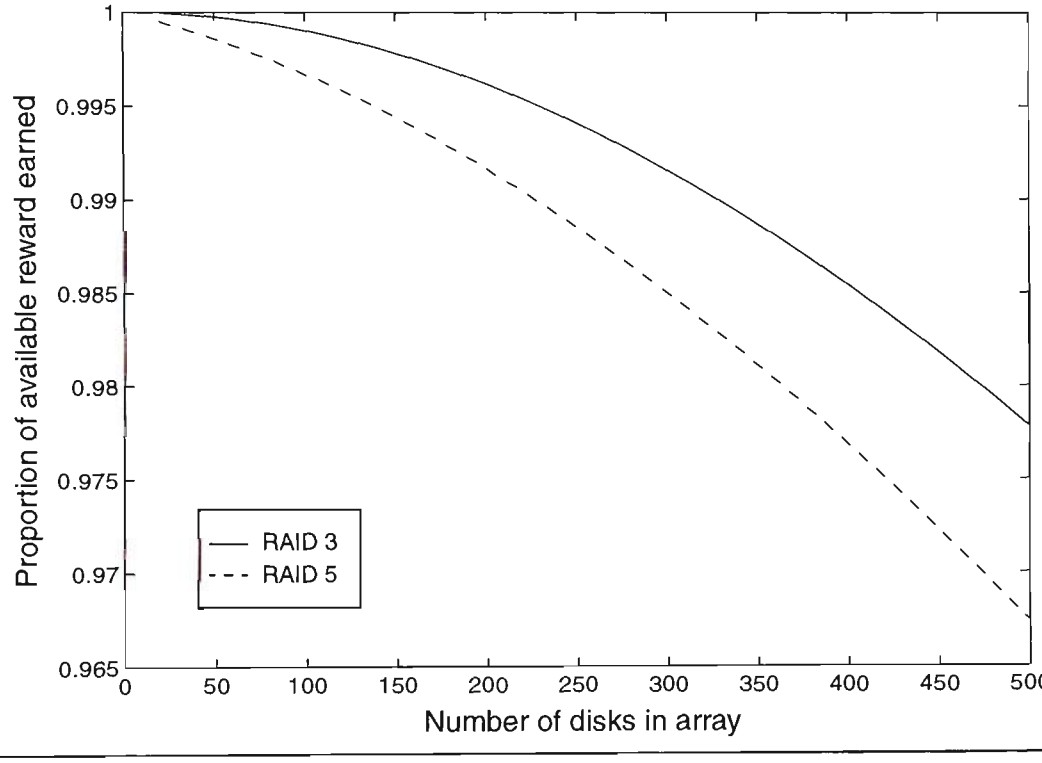


Figure 4.14 Example of reward earned for RAID 3 and RAID 5

ity decreases as we increase the number of disks in the array. The parameters used are MTTF of a single disk of 240,000 hours (10,000 days), mean time to repair a single failure (MTTR(1)) is 1 day and the MTTR a total failure (MTTR(F)) is 10 days. Also as expected, RAID 3 is seen to be consistently earning higher reward than RAID 5. This is obvious, since the reward structure for RAID 3 has all values greater than or equal to those in a RAID 5 array, and all other parameters are identical. When it is considered that for equivalent throughput, a RAID 3 array requires more disks, it will be seen that this result may change dependent on other parameters. This case is considered in the next section.

4.6 Case Studies

Figure 4.14 compares the performance of RAID 3 and RAID 5 for equivalent size arrays. This is not a particularly useful comparison since such arrays don't have the same throughput capability. In the following case studies we consider a more realistic case by fixing the throughput and capacity and determining the number of disks required in each case from Equation 4.7 and Equation 4.8.

4.6.1 Effect of Disk Reliability

Modern disks have a considerable range of quoted reliability figures of merit. As already mentioned, the typical figure of merit is quoted as a mean time to failure (MTTF). [Gang94] states that typical MTTF values for modern disk drives range from 200,000 to 1,000,000 hours. Given the heavy load that disks in a video server will be under, however, the authors feel that this range may be overly optimistic. As such we reduce this and consider 240,000 hours as the upper limit of reliability of a single disk. We consider a case where the peak throughput requirement of a single array is 500 streams. From the method used in Section 4.4 we can thus determine that the RAID 5 array requires 72 disks while a RAID 3 array will require 207 disks to meet this demand. Notice that this difference is not directly proportional to the cost difference of the two systems, since the buffering requirements and disk capacities also differ.

The graph shown in Figure 4.15 compares the reward earned for RAID 3 and RAID 5 disk arrays for a variety of MTTF values of single disks and two full system repair times. In each case the MTTR(1) is 1 day (24 hours). The results are presented in terms of the proportion of the maximum reward that was earned by either system. In the case of 2 day total system repair time (the lines marked with crosses) it is observed that for low disk reliabilities (the left side of the graph) the RAID 5 system earns more reward since it requires fewer disks, and as such is less likely to suffer disk failures. As reliability of indi-

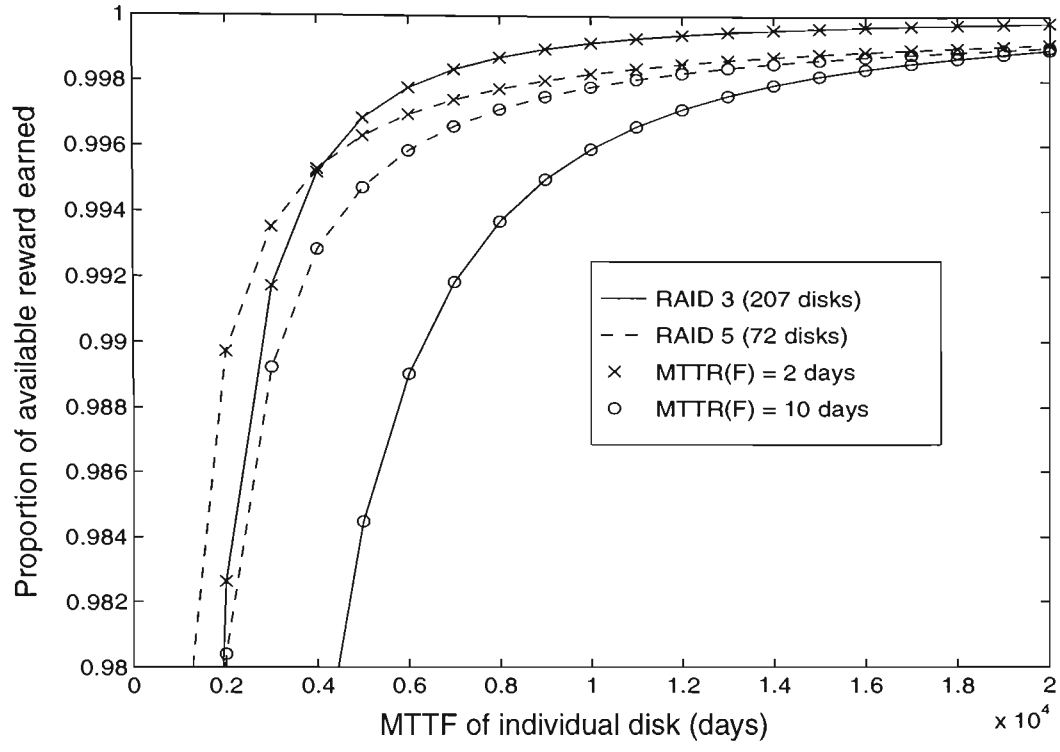


Figure 4.15 Reward earned vs MTTF for throughput of 500 streams

vidual disks improves, however, RAID 3 becomes the superior performer, due to the small proportion of time spent in the totally failed state and the higher reward structure of RAID 3 in state 1 (partially failed). When total repair time is increased to 10 days, it is observed that for the range of disk reliabilities shown here (which range from pessimistic to above average) RAID 3 never earns more reward than a RAID 5. In either case, when the extra cost of RAID 3 is taken into account, it appears that RAID 5 provides the most cost effective storage system for interactive video servers. In the next section, maintenance costs are accounted for before presenting conclusive comparisons of the two RAID levels.

4.6.2 Maintenance Costs

Another important factor to consider in the cost comparison of the two systems is maintenance costs. As a very minimum the cost of a replacement disk is incurred every time a disk fails. The number of

disks that fail (and hence the number that must be replaced) over a given period can easily be determined from the following equation.

$$\text{Number of Failed Disks} = \frac{tD}{MTTF} \qquad \text{(Eqn 4.56)}$$

And the cost of such failures is ascertained by multiplying Equation 4.56 by K_D. This is of course an underestimate of the total lifecycle costs of either system but it is a useful basis for comparison.

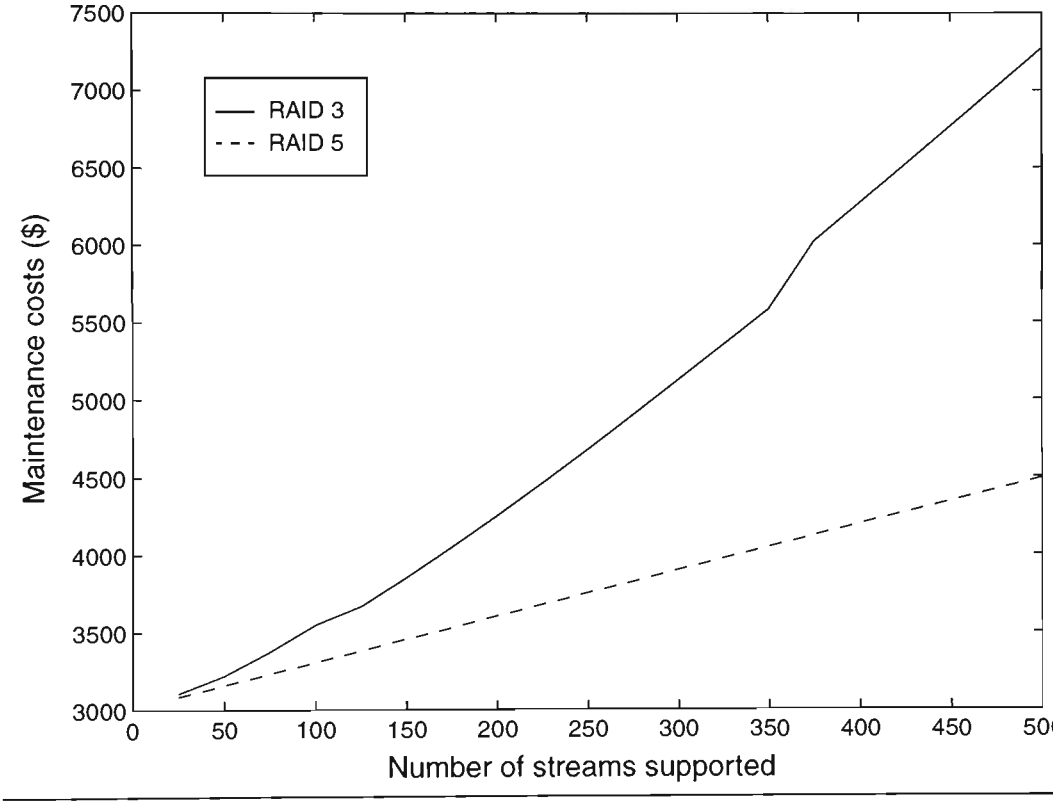


Figure 4.16 Maintenance for a 3 year period for RAID 3 and RAID 5

Figure 4.16 shows the maintenance costs for RAID 3 and RAID 5 for a varying number of streams. We see that RAID 3 has considerably higher maintenance costs than RAID 5 since it requires a larger number of disks to support a given throughput. Note that the variation of costs with a varying number of streams is not as steep as might be expected. This is due to the additional requirement of providing a minimum of 100GB of storage capacity.

4.6.3 Cost vs Revenue

As a final comparison of RAID 3 and RAID 5 we compare the total cost and the revenue earned by the systems over a fixed period. Assume that a system remains in service for 3 years, which is a reasonable lifecycle period for computer related equipment. A MTTF per disk of 240,000 hours is assumed and a MTTR(1) of 24 hours and MTTR(F) of 240 hours. We then calculate the revenue earned as the product of the total available revenue (from the viewer profile used earlier, Figure 4.7), the years of operation (3), the cost per viewer hour ($5) and the proportion of the reward earned by the particular system. The cost of the system is calculated as discussed in Section 4.4.

The graph in Figure 4.17 compares the difference in revenue earned over a 3 year period with the total operating cost of RAID 3 and RAID 5 systems. The chain line represents the revenue earned by a RAID 5

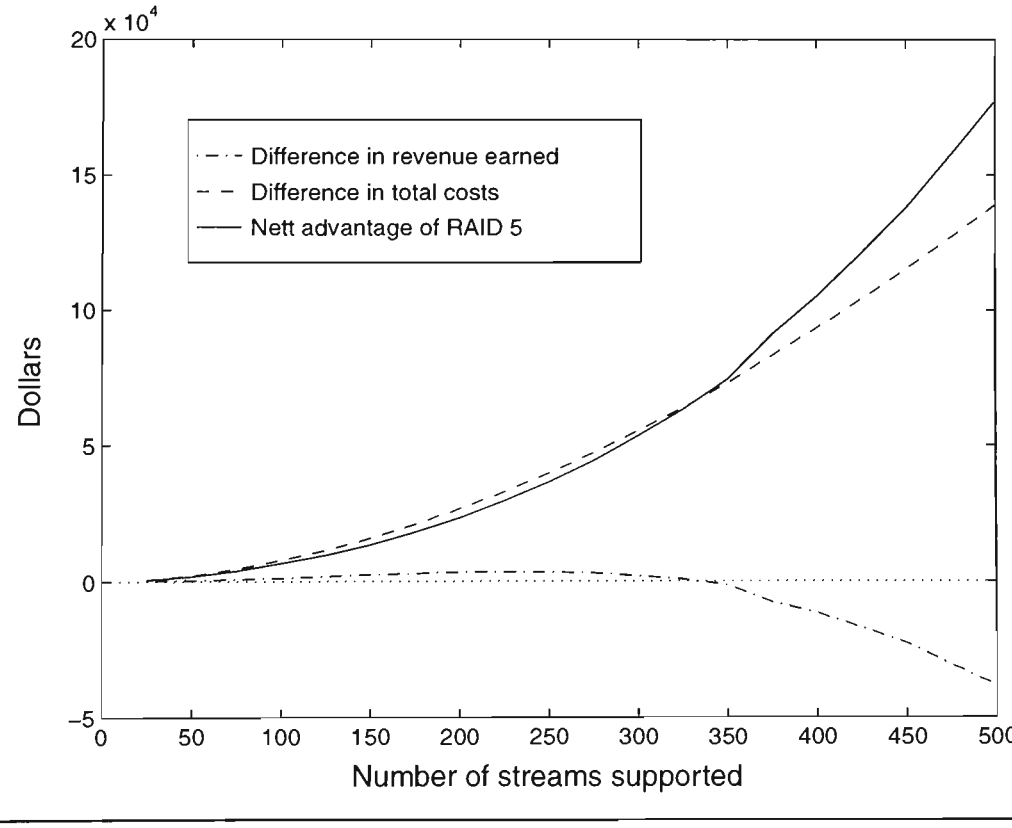


Figure 4.17 Revenue earned and total cost difference vs streams supported

array subtracted from that earned by a RAID 3 array over a 3 year period. For low throughputs the RAID 3 earns more than the RAID 5 array. This is because both arrays are quite small and hence very reliable and the reward structure of the RAID 3 is superior to that of the RAID 5. However, as the throughput requirement increases, the number of disks in the RAID 3 increases much faster than the RAID 5 and as such the RAID 3 becomes less reliable than the RAID 5. Hence for large arrays, the RAID 3 array actually earns less revenue than the RAID 5. The broken line shows the total operating cost of a RAID 5 subtracted from that of a RAID 3 array. This incorporates the initial cost and maintenance costs discussed earlier. As expected, the RAID 3 costs are always higher than RAID 5 and as such the curve is always positive valued. This is because the smaller disks used by the RAID 3 system are actually more expensive per unit of capacity. The overall result is summarized by the solid line which shows the actual increase in profits to be gained by using a RAID 5 disk array over using a RAID 3 disk array. It is, of course, the subtraction of the chain line from the broken line. This nett advantage is observed to be constantly positive implying that for all capacities considered here, the RAID 5 system is more cost effective than the RAID 3. Indeed, once we reach a throughput of just 500 streams, the RAID 5 architecture provides a $180,000 dollar advantage. When we realise that a peak throughput of 500 streams equates to a viewer population of approximately 1,200 people (assuming 40% peak activity as suggested by Figure 4.7), we see that this is a large cost advantage in favour of RAID 5. Over a 3 year period we can expect to increase profit by approximately $150 per viewer merely by choosing a RAID 5 architecture. Considering that video services will likely be utilised by millions of people this equates to total savings of millions of dollars for service providers.

As mentioned in Section 4.4 it is possible that buffering will not necessarily be incorporated in the server, but instead the cost may be borne by the user with the buffering contained in the STB. As such

in Figure 4.18 we show the results from the same analysis as above, excluding buffering costs. It is clear that even excluding buffering costs, the RAID 5 system is preferable in terms of financial profits earned over a three year period.

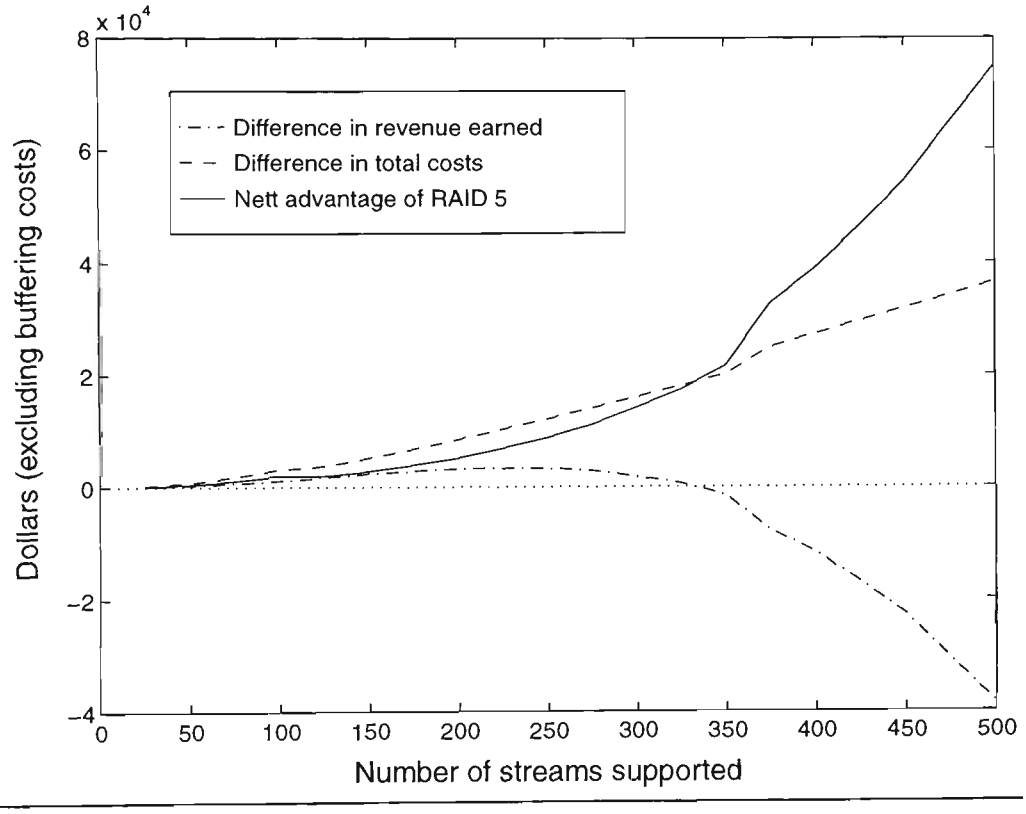


Figure 4.18 Revenue earned and total cost difference (ignoring buffering) vs streams supported

4.7 Conclusion

Video servers will rely on disk array technology to at least provide the core of the capacity and bandwidth requirements of interactive applications. Each server is likely to consist of multiple disk arrays, each storing a number of titles and serving a proportion of the viewer customer population. Previous literature has focused attention on using disk arrays to gain the performance required for interactive video applications. The consideration of appropriate architectures to provide high reliability as well as performance has received little attention. Indeed, recently RAID levels have been selected almost

arbitrarily and poorly justified [Chan95] [Cohe95] [Ng92] [Orji96] [Toba93].

This chapter has examined the available options for high reliability disk arrays, focusing on RAID 3 and RAID 5 as the two most suitable candidates and those receiving most attention in existing literature. The combination of performance and reliability constraints lead to the use of performability modelling which is a technique well established in other fields. An analytic model of performability was derived and validated against simulation results for the architectures of interest. The robustness of the analytical model was also confirmed by relaxing many of the assumptions made in the analysis and showing that simulation results still only varied marginally from those of the analysis. Further, this model (in combination with a cost model of RAID 3 and RAID 5 arrays) was used to show the superior performance of RAID 5 arrays under a wide range of operating conditions. This conclusion is supported by [Ng89] and [Seo95] which state that the high concurrency of a RAID 5 organisation should indeed lend itself to the environment where many moderate bandwidth streams are required to be supported. RAID 3 on the other hand may be more beneficial in other environments not related to interactive video servers.

Chapter 3 has considered network issues relating specifically to server and cache placement for maximum cost effectiveness. This chapter has compared options for storage provision within any given server and determined quantitatively that a RAID 5 organisation is considerably more cost effective than a RAID 3 organisation given the same constraints. In the next chapter we consider object allocation to disk arrays within a video server. In other words given a set of objects with associated storage and bandwidth requirements, how can they be allocated to disk arrays within the server to guarantee a high-level of utilisation of all arrays within the server.

5. Object Allocation for Disk Array Based Video Servers

Seek simplicity but distrust it.

- A. N. Whitehead

5.1 Introduction

This chapter presents an efficient scheme for utilising homogeneous disk arrays for video server provision. Chapter 2 identified hierarchical approaches proposed in the literature as the most intuitive solution to the problem of highly variable movie popularities. In Chapter 3 this idea was refined to utilise varying disk capacities in order to provide a storage hierarchy by way of heterogeneous disk arrays. Unfortunately, this method (although unique and certainly preferable to many other types of storage hierarchy) still suffers from inefficiencies due to the partitioning of storage into fixed groups. In this chapter we identify the homogeneous approach as a preferable solution to the storage problem. The chapter goes on to present schemes to ensure efficient utilisation of the homogeneous disk arrays for a wide range of input parameters.

In Section 5.2 the differences between heterogeneous and homogeneous storage are illustrated, highlighting the potential benefits of the homogeneous approach. A mathematical description of the resulting object allocation problem follows in Section 5.3. One important figure of merit of a video server is blocking probability and

any solution to the object allocation problem must provide some sort of guaranteed level of blocking probability, this is discussed in Section 5.4. An examination of the allocation problem reveals an analogy with the two dimensional vector packing (2DVP) problem of operational research and this fact along with its consequences, is presented in Section 5.5. Section 5.6 presents upper bounds and tight lower bounds for the allocation problem before considering the performance of various heuristic solutions and proposing a new heuristic (SSBF) in Section 5.7. Numerous case studies are conducted in Section 5.8 which serve to demonstrate the quality of the heuristic proposed here, especially when compared with existing heuristics from the literature.

5.2 Homogeneous vs Heterogeneous Disk Arrays

Chapter 3 presented an extension on previous literature in an effort to solve the problem of storing movies with varying popularities. The method involved using heterogeneous disk arrays to provide a form of hierarchical storage. In essence, small capacity disks resulted in high bandwidth to capacity ratio storage suitable for storing popular movies, whilst larger disks gave the opposite result and were used for the less popular movies. Provided appropriate disk sizes were selected and movies were grouped according to popularity, the algorithms presented gave an efficient solution to the storage problem.

The heterogeneous disk array approach, however, is not without its drawbacks. Primarily, this is the same drawback as experienced by all hierarchical storage systems. That is, the inflexibility caused by the fixed partitioning of storage space into several levels. For example, 50 GB of storage might be allocated to the few popular movies, 200 GB to less popular movies and 800 GB to the large group of least popular movies. This decision must be made at design time and is not easily modified as movie popularities change. It is easily conceivable that the actual movie popularity distribution will change

with time and from one application to another, and such a rigid storage structure will tend to cope poorly with this. In this chapter we propose a homogeneous storage system to overcome this deficiency.

Essentially a homogeneous storage server consists of a set of disk arrays all with identical throughput and capacity capabilities. In other words. all arrays are constructed from the same number of the same disk drives. In order to utilise these arrays efficiently, it will be necessary to place popular movies together with unpopular movies on the one array to ensure that neither bandwidth nor capacity resources are wasted. This replaces the hierarchical storage policy, whereby all popular movies are stored together on a single array, less popular movies on the next array and so forth. The principle advantage of this homogeneous approach is that, provided the placement algorithm is efficient, the same disk arrays will be just as suitable regardless of the movie popularity distribution. Provided the ratio of total capacity and bandwidth requirements of all the movies to be stored is a good match to the bandwidth and capacity available at the server, the actual popularity distribution of the movies is irrelevant. The validity of this statement will be demonstrated by the case studies presented in Section 5.8. A similar idea is presented in [Litt95], where it is shown that for maximum efficiency movies should be allocated to disk arrays in order to ensure that the disk arrays are all equally likely to be accessed. Unfortunately, [Litt95] does not provide a method for ensuring that this is the case. In the following sections heuristics are presented which achieve precisely that aim.

Figure 5.1 illustrates the essential difference between heterogeneous and homogeneous storage solutions, for the simple case of three disk arrays and six movies to be stored. The movies are assumed to be of unit length (occupying one unit of disk capacity) and popularities following a simple linearly decreasing distribution. Although extremely simplistic this diagram does serve to illustrate the key difference between heterogeneous and homogeneous approaches. In this case

both systems gain the same efficiency (100% utilisation of both resources) and have the same cost, but the heterogeneous system groups movies together according to popularity and stores them on an appropriately sized storage device, while the homogeneous approach groups movies together in such a way as to make optimum use of a single type of storage device.

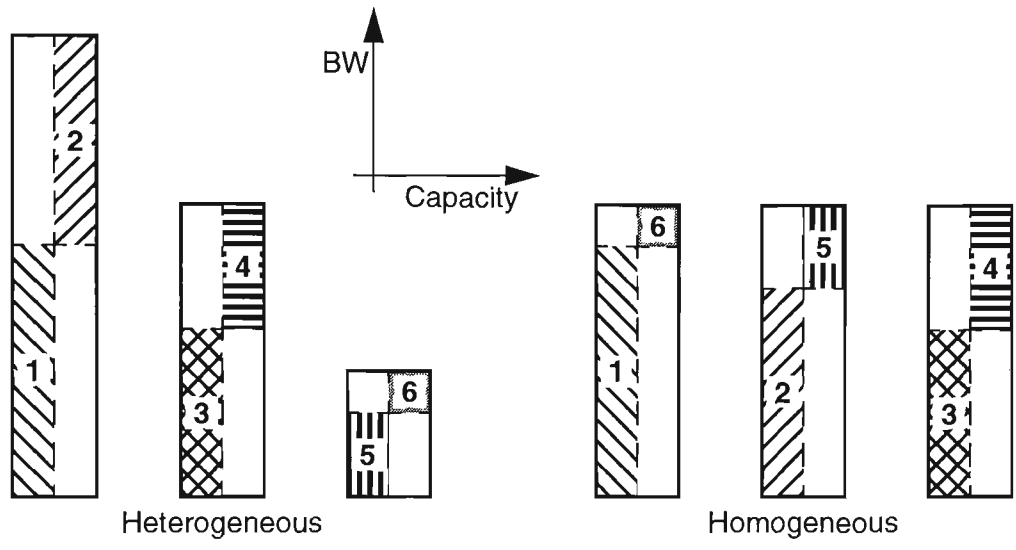


Figure 5.1 Illustration of heterogeneous and homogeneous disk striping.

There has been little work explicitly considering the issue of allocating objects to disk arrays in interactive video systems. It will be seen that this problem does, however, have similarities with bin-packing problems and heuristics for this problem will be discussed later (Section 5.7.1). In a recent paper [Mour96] proposes an heuristic that is a simple variant of the FFD algorithm (see Section 5.7.1), where it is assumed that all objects have identical capacity requirements. The proposal does not, however, state when a new array should be started while allocating objects, and no results are given in the paper to demonstrate the quality of the heuristic.

As already mentioned [Litt95] considers the problem of object allocation and shows the benefits of allocating objects to arrays to ensure an equal probability of access to all arrays, in terms of a reduced

blocking probability. A method for achieving this goal, however, is not provided.

[Dan95b] is the only other work to address the problem of object allocation to disk arrays. In that paper the authors introduce the Bandwidth to Space Ratio (BSR) heuristic which allocates objects to storage devices such that the bandwidth to space ratio of the object is a close match to that available on the device. The work discussed below was performed concurrently and independently of that reported in [Dan95b] and differs significantly. Specifically, Dan et al. assume constant object capacity requirements, do not account for blocking and take an on-line approach which makes it more difficult to find optimal solutions. Further in [Dan95b], object duplication is advocated to aid in the packing, without considering the cost of this replication. Unfortunately, specific details of the heuristic used are absent from [Dan95b] making a quantitative comparison of their scheme with ours impossible.

The next section presents a mathematical description of the homogeneous object allocation problem.

5.3 Mathematical Description

The problem of optimally allocating objects (movies) to homogeneous disk arrays can be described mathematically as follows.

$$\text{minimise } Z = \sum_{k \in \boldsymbol{K}} D_k \qquad \text{(Eqn 5.1)}$$

subject to:

$$\sum_{j=1}^{N_k} b_{M_{jk}} \leq (BD_k)' \qquad \forall k \in \boldsymbol{K} \qquad \text{(Eqn 5.2)}$$

$$\sum_{j=1}^{N_k} c_{M_{jk}} \leq CD_k \qquad \forall k \in \boldsymbol{K} \qquad \text{(Eqn 5.3)}$$

$$\sum_{k \in \boldsymbol{K}} N_k = I \qquad \text{(Eqn 5.4)}$$

$$D_k \leq S \qquad \forall k \in \boldsymbol{K} \qquad \text{(Eqn 5.5)}$$

Table 5.1 Definition of symbols for optimisation

I	set of movies **I** = {1,2,...,I}
K	set of striping groups **K** = {1,2,...,K}
N_k	movies on striping group k
D_k	disks in striping group k
M_{jk}	index of jth movie on kth striping group
b_i	bandwidth requirement of movie i
c_i	capacity requirement of movie i
B	bandwidth of a single disk
C	capacity of a single disk
S	maximum allowable striping group size

These equations define the objective function and constraints of the optimisation problem described above. Equation 5.1 is the objective function and states the aim to minimise the total number of disks required, and as such minimise the cost. In Equation 5.2 and Equation 5.3 bandwidth and capacity limitations of each striping group are accounted for, ensuring that they cannot be exceeded by the objects stored on them. Note that the prime (') on the BD_k is intended to signify that the raw bandwidth of the array has been converted to an effective bandwidth in accordance with the required blocking probability as discussed in Section 5.4. Equation 5.4 guarantees that the entire movie population under consideration is stored somewhere on the server, while Equation 5.5 enforces an upper limit on the number of disks that can be in any single striping group. It should be noted that the subscript on the D implies that different arrays may have different numbers of disks. This variation of the homogeneous scheme is not considered further in this thesis, but some results obtained from such a system can be found in a previously published paper of the author [Barn96e]. The value of the upper limit on array size, S, can be derived from the availability requirement of the server (see Chapter 4 and Chapter 7 for an exam-

ple) or from an implementation constraint imposed by the disk array controllers or system architecture.

It can be shown that this optimisation is NP-hard (since it is analogous to the bin-packing problem (see Section 5.5)) [Gare76] [Litt95] which implies that it cannot be solved for global optimality in polynomial time. In other words, the complexity of the optimisation increases more than polynomially with the number of objects to be allocated. The most useful approach to such NP-hard problems is generally to apply heuristic solutions which may be either general or problem specific [Telf94]. This thesis focuses on problem specific heuristics which utilise detailed information about the problem to rapidly obtain near-optimal solutions.

5.4 Blocking Probability

Figure 4.7 in Chapter 4 shows the average user profile versus time of day for television viewing in Sydney, Australia. From this and the popularity distribution of movies it is possible to ascertain the busy hour average load that will be placed on each individual movie. In order to ensure a certain level of service availability, blocking probability of the server during this busy hour should be restricted below a given level.

Blocking probability will be determined by modelling a single disk array as a multiserver queue. Since a video server is connected to a large viewer population it is assumed that the interarrival time of new requests is Poisson distributed.

The service time distribution is more difficult to model. Of course the service time equals the time that a viewer remains in service. This is primarily related to the length of the movie being watched. However, as discussed in [Li96] the mapping from movie length to service time is perturbed by interactivity functions such as pausing, rewinding and fast-forwarding. Given also, (as shown in Section 5.5.1) that

movie length can be approximated by a Gamma distribution, it is clear that the queueing model must assume a general distribution for service time.

For the purposes of blocking probability calculations, it is assumed that there is no waiting room within the server. This assumption is made to give a worst-case bound on blocking probability. Depending upon the willingness of customers to wait for admission, some waiting room (ie. queueing) is actually likely to be provided. By assuming no waiting room, the blocking probability derived here is an upper bound on any real system's blocking probability. For our purposes a customer is considered blocked if they cannot immediately be allocated a server upon arrival. Following this definition, it is clear that in order to determine blocking probability, a disk array can be modelled as an M/G/m/m queue[1]. Modelling an entire array as a single M/G/m/m queue does implicitly assume that a customer can be admitted to any free server in the queue. In reality this is not the case as a user must wait until a slot becomes free on the individual disk that contains the start of the desired movie. Effectively this model assumes that the load is relatively well balanced across the array and that a user will be willing to wait until a slot becomes available on the appropriate disk. Such an assumption is reasonable, and this issue is discussed further in Chapter 6.

An approximation from [Whit84] states that if Y_α is the equilibrium number of busy servers in a G/GI/m/m queue, then:

$$P(Y_\alpha = k) \approx \frac{P(X_\alpha = k)}{P(X_\alpha \leq m)} \qquad \text{(Eqn 5.6)}$$

where X_α is the equilibrium number of busy servers in a G/GI/∞ queue. Note that the α in the subscript is the queue utilisation in each case.

1. Note that the second "m" in M/G/m/m is replaced by 0 in some notations representing 0 waiting room [Whit84]. Here the second "m" is used to indicate that there are m total spaces available in the system, including the m servers implied by the first "m".

Given that our arrival process is assumed to be Poisson, the X_α queue can be modelled by an M/G/∞ queue which has a known probability of state given by:

$$P(X_\alpha = k) = p_k = (\alpha^k/k!)e^{-\alpha} \quad \text{(Eqn 5.7)}$$

From this expression the blocking probability of our M/G/m/m queue can be calculated from:

$$\begin{aligned} P(Y_\alpha = m) &\approx \frac{P(X_\alpha = m)}{P(X_\alpha \le m)} \\ &= \frac{(\alpha^m/m!)e^{-\alpha}}{\sum_{i=0}^{m} (\alpha^i/i!)e^{-\alpha}} \\ &= \frac{(\alpha^m/m!)}{\sum_{i=0}^{m} (\alpha^i/i!)} \end{aligned} \quad \text{(Eqn 5.8)}$$

which is merely the Erlang-B formula for an M/M/m/m queue [Klei75]. This result implies that the Erlang-B formula can be applied to an M/G/m/m system with good accuracy. Note that the Erlang-B formula was assumed to be a suitable model for blocking probability in a server in [Litt95], although this was never actually shown to be the case.

To confirm the quality of the fit for the situation considered here, an event driven simulation was used to determine blocking probability assuming Gamma distributed service times (see Section 5.5.1) and Poisson arrivals (Figure 5.2).

Figure 5.2 reveals that the Erlang-B (M/M/m/m) approximation for blocking probability is an excellent fit for a wide range of utilisations and server sizes. Although not presented in detail here, several other service time distributions have been studied, and in each case the Erlang-B formula is seen to given an excellent approximation to the blocking probability.

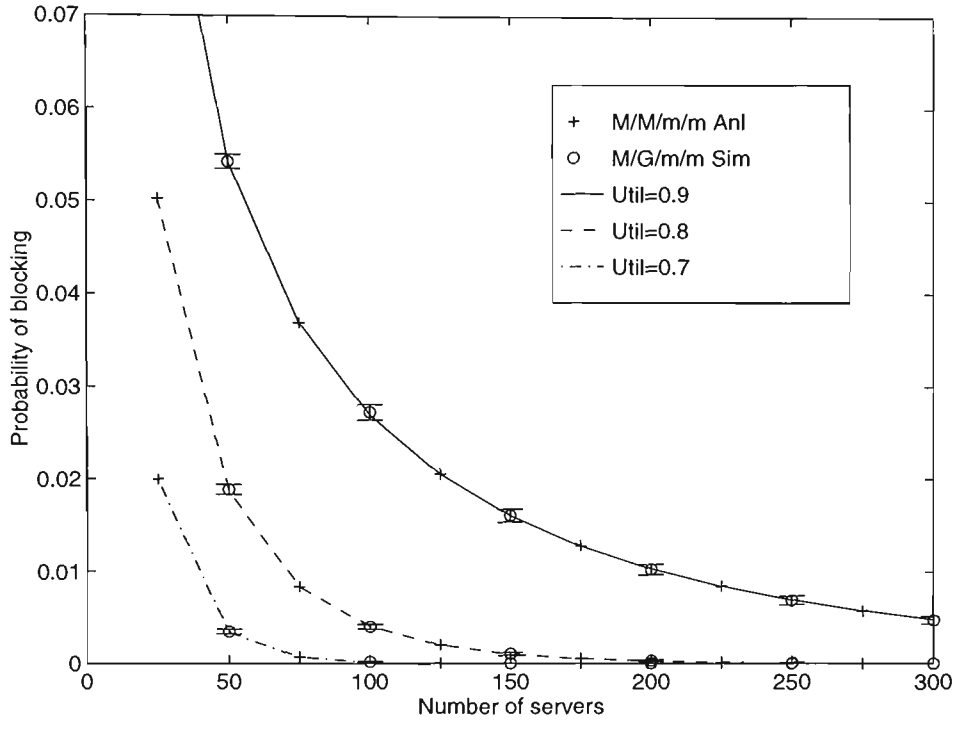


Figure 5.2 Comparison of models for blocking probability

5.4.1 Effect on Disk Array Throughput

Rearranging the Erlang-B formula (numerically) it is of course possible to determine the number of streams that a given array (with a certain bandwidth) should be allocated in order to guarantee (statistically) a certain blocking probability. This effectively maps the bandwidth of a particular disk array determined by the methods of chapter 4 into a (usually lower) value which can be used in the object allocation methodology presented next.

Figure 5.3 shows the ratio of bandwidth in the video server to average viewer load for a range of video server sizes and blocking probabilities. As an example of the mapping from average load to video server requirements, consider the case where a load of 200 streams is to be supported with a 1% blocking probability. From the figure it can be inferred that the server will be required to support 1.1 times this load, or more accurately a total of 221 streams. Conversely, a server capable of supporting 221 streams should only be loaded with

objects with a total "busy hour" requirement of 200 streams in order to guarantee a 1% blocking probability. Hereinafter the figure of 200 streams for this array is referred to as the "effective bandwidth" of an array with a "raw" bandwidth of 221 for a blocking probability of 1%.

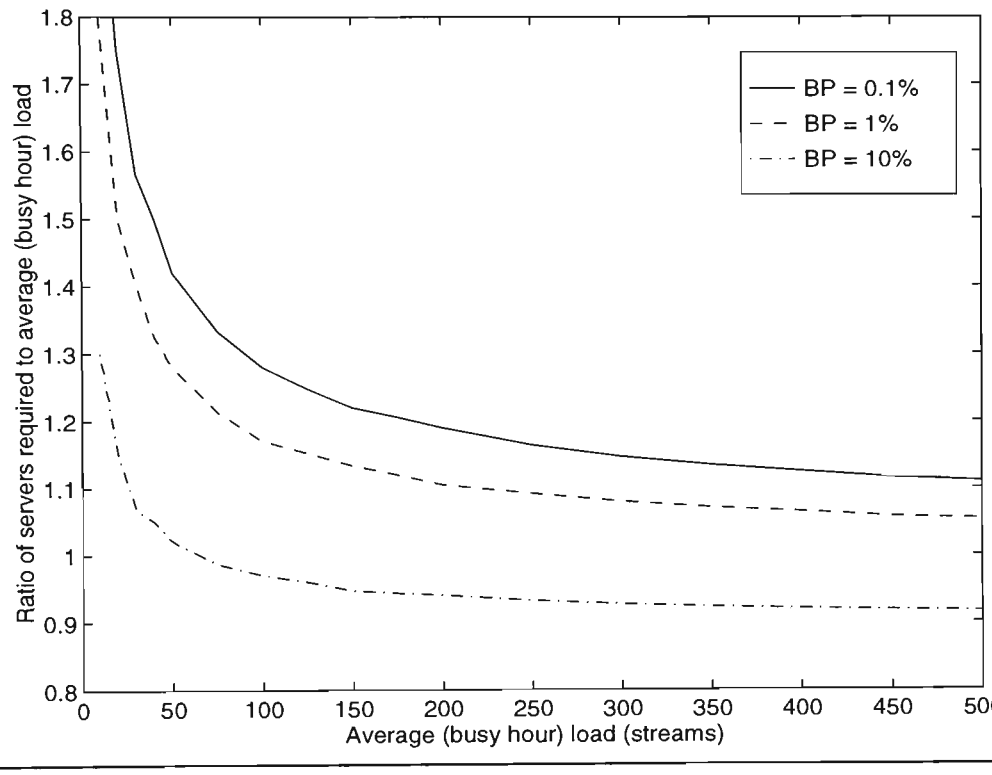


Figure 5.3 Statistical multiplexing for various allowable blocking probabilities in a disk array based video server

Predictably, larger arrays have a statistical multiplexing advantage over smaller arrays in that a smaller increase is required in the number of servers to guarantee a given blocking probability. In other words, larger arrays have a higher ratio of effective bandwidth to raw bandwidth. Unfortunately this result is in direct opposition to the performability analysis of the preceding chapter, which concluded that large arrays are less reliable than small arrays. Although both of these conclusions are intuitively obvious, an effective design must aim to use the quantitative results of each of these aspects to strike an effective trade-off between the two constraints of efficient multiplexing and high reliability. This trade-off is discussed further in the case study of Chapter 7. The next section reveals how this problem is directly related to the two-dimensional vector packing problem

that is a variant of the well-studied bin-packing problem of operations research.

5.5 Two Dimensional Vector Packing Analogy

The optimisation problem defined by Equation 5.1 to Equation 5.5 is NP-hard [Litt95], and given that a server will be required to store potentially thousands of movies with rapidly time-varying requirements, this poses a large problem. The use of heuristic techniques is aimed at providing near-optimal solutions in a reasonable amount of computation time.

Considering that we are attempting to pack a group of movies with bandwidth and capacity requirements onto disk arrays with a certain effective bandwidth and capacity capability, we see that there is a close analogy between this problem and traditional bin-packing problems. A graphical representation (Figure 5.4) serves to solidify the relationship.

Note that in Figure 5.4 the raw bandwidth of the disk array is suitably scaled to give an effective bandwidth according to the desired blocking probability as discussed in Section 5.4. From Figure 5.4, we see that this movie allocation problem is directly analogous to a 2-dimensional vector packing (2DVP) problem [Coff84]. The difference between vector packing and rectangle packing is that, in vector packing, the rectangles can only be packed diagonally and not into the off-diagonal free space. Using rectangle packing in the above situation would clearly result in capacity and bandwidth being "double-booked" to a number of movies. Vector packing appears to be a considerably easier problem to solve than the similar rectangle packing problem. Unfortunately, in comparison to the rectangle packing problem, little work has been produced on the solution of the vector packing problem. A discussion of the literature relevant to the 2DVP problem is presented in Section 5.7.1.

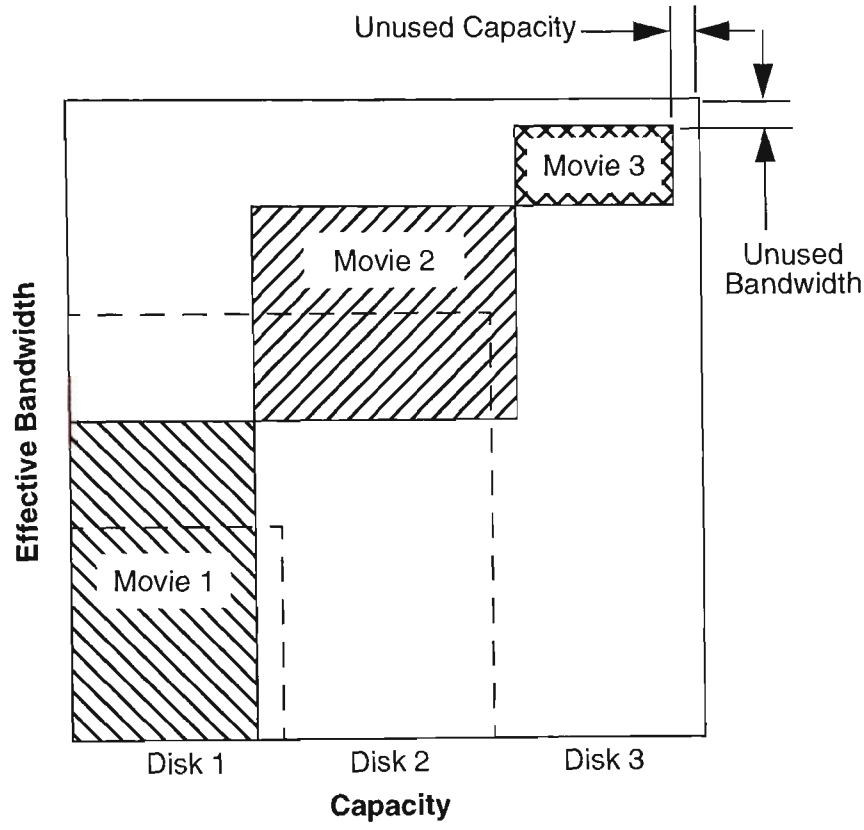


Figure 5.4 Allocating movies to a striping group with three disks

It is important to note that the graphical representation of the problem shown in Figure 5.4 is in no way representative of the physical allocation of movie objects to disk arrays. As discussed earlier (see Section 4.4) movies are allocated to disks in the array in blocks, where each block represents a very small segment of the movie. By using this placement method the array is able to provide approximately D times the bandwidth and capacity of a single disk. It is this increase in available resources supplied by disk arrays that is utilised by the packing approach. It should further be noted, however, that the factor of D increase in bandwidth is only available provided that the load on the array is evenly balanced across all disks in the array. Under certain conditions this may not be the case and the problem of maintaining load balance becomes important. This issue is considered for the coarse-grained RAID 5 disk array in Chapter 6.

Given that the optimisation problem is so readily identifiable as a variant of the vector packing problem, it would seem reasonable to

apply similar problem specific heuristics to solve it. Although general heuristic approaches, such as simulated annealing, genetic algorithms, tabu search and others could also be applied (as they can to almost any optimisation problem), in a case where problem specific information is available, tailored heuristics generally lead to faster and/or better solutions to a given problem [Telf94]. Before considering existing heuristics for the 2DVP problem let us first revisit and identify the important input parameters.

5.5.1 Input Parameters

The major input parameters for the packing problem are movie length and popularity and disk array capacity and bandwidth. Of these, only movie length has not so far been considered in detail in this thesis. Although the object size distribution will vary depending on the application, entertainment style video-on-demand is again considered as a typical example. Making this assumption enables statistics to be gathered on existing movies with a high degree of confidence that these statistics will also apply to future video-on-demand systems. Statistics for other future interactive video services are much more difficult to estimate.

Movie length data was collected from a movie database containing over 23,000 movies. Titles with lengths greater than 180 minutes or less than 50 minutes were discounted since a number of entries in the database were actually television series' or short silent films. This left over 22,000 movies with lengths within the desired range. From this raw data, a histogram was generated and the method of maximum likelihood estimators [Law91] was used to fit several common distributions to the raw data. Of these, the Gamma distribution (shown in Equation 5.9), with parameters α=18.48 and β=5.06, was seen to give the best fit to the existing data.

$$f(x) = \begin{cases} \dfrac{\beta^{-\alpha} x^{\alpha-1} e^{-x/\beta}}{\Gamma(\alpha)} & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases} \qquad \text{(Eqn 5.9)}$$

It should be noted that standard goodness-of-fit tests (for example, Chi-square) are difficult to apply to large datasets such as this one, as they will almost always reject the hypothesis based on a relatively small number of mismatches [Gibb85]. As such, for the purposes of this investigation, a graphical comparison is used. Figure 5.5 shows a histogram of the data and the fitted Gamma distribution, as well as cumulative frequency in each case. It can be seen from the figure

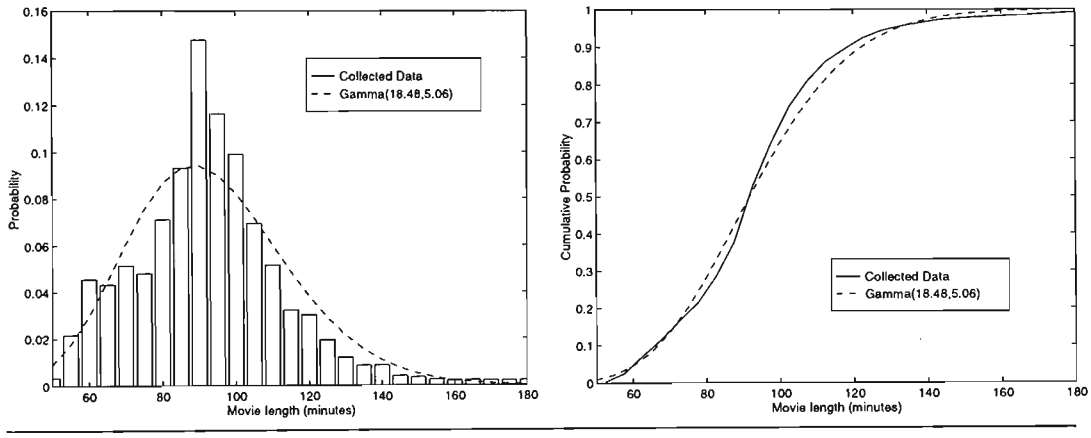


Figure 5.5 Probability density and distribution functions for movie length data and the Gamma(18.48,5.06) distributions.

that the Gamma distribution is a good fit to the empirical data with the possible exception of the peak between 90 and 100 minutes. Clearly, a large proportion of movies have a duration somewhere in the vicinity of 90 and 100 minutes, accounting for this peak. Such a rapid change is impossible to model with a standard distribution. It must also be noted that in addition to the Gamma model derived here, several other models for object length will be used in the comparison of the packing heuristics in Section 5.8, in order to extend the range of validity of the results obtained.

The other three important input parameters have already been presented earlier in the thesis. Movie popularity will be modelled by the heavily-skewed long-tailed models seen in the literature as dis-

cussed in Section 3.4.1. Disk array bandwidth depends on the number of disks, and the block sizes used in each case. From the results of Chapter 4, it is assumed that for coarse-grained arrays considered here, an individual disk can sustain a throughput of about 20 Mbps. The selection of disk capacity is made so as to ensure that the ratio of disk capacity to bandwidth matches that of the total movie population in a similar manner to the heterogeneous arrays of Chapter 3. The difference here is that all the arrays use the same disks and as such maintain the same ratio of capacity to bandwidth.

5.6 Upper and Lower Bounds

Before presenting and evaluating the performance of various heuristics for the movie allocation problem, bounds are required to provide a quantitative measure of their performance. A simple upper bound on performance is obtained by considering the maximum of the bandwidth and capacity requirements for each movie and allocating the appropriate number of disks for this movie. A physical realisation of this would result in each movie being stored on a separate disk array, with no movies sharing resources. Depending on the input distributions this can be hugely wasteful, although a similar approach works well in the heterogeneous disk array approach since disk size is varied to match the required capacity to bandwidth ratio of each object (or group of objects). This upper bound can be represented by:

$$Z_{UB} = \sum_{i \in I} \left\lceil \max\left(\frac{b_i}{B}, \frac{c_i}{C}\right) \right\rceil \qquad \text{(Eqn 5.10)}$$

The most obvious lower bound is obtained through similar reasoning. If all movies were to be stored on a single disk array, then the number of disks in that group would only need to be large enough to meet the largest of the sums of the requirements in each dimension.

$$Z_{LB1} = \left\lceil \max\left(\sum_{i \in I} \frac{b_i}{B}, \sum_{i \in I} \frac{c_i}{C}\right) \right\rceil \quad \text{(Eqn 5.11)}$$

Although this lower bound is generally tight, another bound is suggested in [Spie94] which under certain conditions can produce a tighter lower bound (ie. a higher array count). In the case where some of the objects are very "large" in one or both dimensions while many are small, then only a few of these large objects will fit on each array. The popularity of video objects fits this scenario due to it's heavy skew. In such cases Equation 5.11 can seriously underestimate the true lower bound.

The algorithm presented in [Spie94] attempts to find a set of objects, no two of which can be placed in the same bin. Clearly once this set has been found, the number of elements in the set represents a second lower bound. The technique of finding such a set can be thought of in graph-theoretic terms where each object is a vertex and edges exist between all pairs of objects that exceed the array capacity in either dimension. The problem is then one of finding the clique in the graph with the largest number of vertices. Note that in general, this problem is itself NP-hard, but due to the nature of this graph (a 2-threshold graph) a solution can indeed be found in polynomial time by using an algorithm from [Hamm85]. With this algorithm in place, a second lower bound, Z_{LB2} is obtained, and the overall lower bound for a given problem is clearly the greater of Z_{LB1} and Z_{LB2}.

$$Z_{LB} = \max(Z_{LB1}, Z_{LB2}) \quad \text{(Eqn 5.12)}$$

As shown in Section 5.8, the combination of the two lower bounds given above, does indeed provide a tight lower bound for the comparison of the heuristic procedures presented next.

5.7 Heuristics

With the object allocation problem and lower bounding procedures now well defined, this section examines previous work in the litera-

ture on heuristics for solution of the vector packing problem, and also introduces a new heuristic which aim to provide more efficient solutions by utilising additional knowledge of the actual problem at hand.

5.7.1 Review of Existing Bin Packing Heuristics

As already mentioned, the two-dimensional vector packing problem is essentially just a two-dimensional version of the basic bin-packing problem. The other two-dimensional variant is rectangle packing which has attracted considerably more attention in recent literature (see [Dows92]). This is possibly accounted for by the obvious mass of applications for the rectangle packing problem and other related "knapsack" problems. The applications for the multi-dimensional vector packing problem are somewhat less tangible, but include multi-processor scheduling problems [Gare76] and memory allocation problems [Maru77] as well as the object allocation problem discussed here [Barn96e]. [Coff84] provides an excellent overview of bin-packing research with consideration given to all the common variants of the problem. An indication of the lack of work in vector packing is that of this 58 page survey paper, only 2 pages are allocated to research in the area of vector packing.

Of the results summarised in [Coff84] perhaps the most interesting are those from [Gare76] which discuss the worst case performance of suitably modified First-Fit and First-Fit-Decreasing algorithms. First-Fit (FF) and First-Fit-Decreasing (FFD) are known to be two of the best algorithms for the one-dimensional packing problem, consistently performing close to the optimum. FF simply moves through the object list placing each object into the first bin in which it will fit, with new bins started as necessary. FFD preprocesses the object list, placing the objects in decreasing order of size, before apply the FF heuristic. This modification is shown to give consistent improvement over the original FF algorithm. In the 2DVP case, FFD can sort objects on a number of criteria, such as by the sum of dimensions,

the sum of the squares of the dimensions or the product of the dimensions [Maru77]. The proposal in [Gare76] sorts the object list in decreasing order of the larger of the two (normalised) components of each object, before applying FF. We refer to this algorithm as FFGAR, as this is just one variant of FFD. Another variant considered here is FFSUM [Kou77] which sorts the objects based on the sum of their dimensions.

[Gare76] analyses the worst case performance of the First-Fit algorithms and showed that FF always performs within d+7/10 of the optimum solution and that FFGAR is always between d and d+1/3 of the optimum solution, where d is the number of dimensions in a multi-dimensional vector packing problem. For the 2DVP problem d=2. In other words, [Gare76] has effectively shown that the worst-case performance of the First-Fit algorithms is around a factor of 2 worse than the optimal packing. It must, however, be noted that simulation work by [Maru77] indicates that average case performance of these algorithms does not generally approach this very poor worst case.

Generally, bin-packing research has focused on finding worst-case performance of particular algorithms and developing new algorithms to improve these bounds. While some simulation study has been used to determine average case performance it is important to note the limitations of this work. Specifically, the distributions assumed for object sizes are almost invariably uniform [Spie94] [Mart90]. This is in direct contrast to the very contrived distributions used when demonstrating worst-case bounds. One exception to this is found in [Maru77] where the authors combine sets of uniform random variables so as to form bell-shaped and skewed distributions for object dimensions. These distributions are used because they are believed to be of practical importance rather than because they accurately model a particular case of interest. The effect of variations in these distributions is not well-studied in [Maru77], however. These distributions may seem reasonable when an algorithm is proposed for

general application to a class of problem with no specific application in mind. When a particular application is to be studied, however, (as is the case here) it is important to consider the appropriate input distributions for object sizes. The distributions appropriate for interactive video services were discussed in Section 5.5.1.

In a large set of simulations considering n-dimensional vector packing, [Maru77] presents a generic packing algorithm that can be made equivalent to the common algorithms of next-fit, first-fit, best-fit and so forth. It is interesting to note that the algorithms used are all derived directly from the one-dimensional packing case, even though the worst case analysis of these algorithms indicates that performance can become considerably worse as the dimensionality of the problem increases [Gare76].

[Spie94] explicitly considers the 2DVP problem and applies a general branch-and-bound algorithm in an attempt to improve on prior solutions. For comparison, two adaptations of the first-fit-decreasing algorithm are also considered. Results are obtained by simulation of packings for various numbers of objects with sizes drawn from uniform distributions with several ranges. Of 48 cases considered, the branch-and-bound heuristic produced improved solutions over the FF schemes in only 6 instances, and in 5 of these the improvement was only by 1 bin. When it is considered that the branch-and-bound method can take in excess of 10 hours to generate these improved solutions (versus less than 0.5 seconds in every case for the FF heuristics) the results are not encouraging.

The results of [Spie94] are representative of many of the generally applicable optimisation techniques, which include branch-and-bound, as well as simulated annealing, genetic algorithms and tabu search. The running time of such algorithms is generally not bounded, and is often found to be many orders of magnitude longer than the appropriate problem specific heuristic [Telf94]. Perhaps if

the improvement over other techniques is significant such running times could be justified, but this is not the case in [Spie94].

The next section presents a new problem specific heuristic tailored to the input distributions discussed above. The motivation for this heuristic arises from the poor performance of the existing heuristics for these object types. Table 5.2 illustrates the efficiency of FFGAR and FFSUM as well as the two lower bounds for a variety of cases.

Table 5.2 Performance of FFGAR and FFSUM packing heuristics

x-distn		y-distn		FFGAR			FFSUM		
Dist.	Params	Dist.	Params	lb[a]	bins	% excess	lb[a]	bins	% excess
Uniform	[0,1]	Uniform	[0,1]	530.6	533.4	0.5	534.5	540.2	1.1
Uniform	[0.2-0.8]	Uniform	[0.2-0.8]	541.9	544.8	0.5	539.4	544.9	1.0
Uniform	[0.1-0.4]	Uniform	[0.1-0.4]	252.4	271.5	7.6	252.6	271.5	7.5
Gamma	mn=0.01	Zipf	mn=0.01	10.7	15.8	48	11.3	16.9	50
Gamma	mn=0.02	Zipf	mn=0.02	20.7	29.9	44	20.6	30.9	50
Gamma	mn=0.03	Zipf	mn=0.03	30.6	42.7	40	30.7	44.8	46

a. Note that the lower bounds shown are the greater of lb1 and lb2 as indicated by Equation 5.12. In rows 1 and 2 the tight lower bound was given by lb2 while in the remainder of the rows lb1 gave the tighter constraint.

In each case 10 independent runs were performed, with each run required to pack a total of 1,000 objects. The ranges of uniform random variables have been taken from [Spie94], while the means for the Gamma and Zipf distributions were selected to represent a reasonable number of disk arrays in a video server. These parameters will be discussed in more detail in Section 5.8.

In the case of uniformly distributed object sizes of various ranges (first three rows of Table 5.2), the FFGAR heuristic is seen to perform very well with a mean excess from the lower bound of less than 1% for all the ranges of uniform random variable considered here. This result is in good agreement with the results obtained by [Spie94], where fewer objects are packed, but the FFGAR algorithm always closely approximates the lower bound. Given that most simulation studies to date confine themselves to uniform random varia-

bles, it is understandable that the FFGAR has been believed to be an adequate heuristic.

When object size distributions are changed to more accurately model expected video object sizes in interactive video servers, however, the FFGAR and FFSUM heuristics perform very poorly. As seen in the last three rows of the table, the difference between the lower bounds and the heuristic solutions obtained by the existing algorithms is quite significant. Although this could be attributed to loose lower bounds, improvements to the packing algorithm also warrant consideration. The next section presents a new algorithm (SSBF) and reveals that the lower bounds are actually quite tight and that SSBF approaches these lower bounds.

5.7.2 The Same-Shape-Biggest-First Heuristic

Table 5.2 reveals that the First-Fit based algorithms perform poorly with the input distributions that are appropriate for interactive video servers. Investigation of a simple example provides some enlightenment as to why this is the case.

First we adapt the notation used in Table 5.1 to the case where the bin dimensions (ie. disk capacity and bandwidth) are both normalised to 1. This clearly requires the movie dimensions to be suitably normalised. Let each object x_i have dimensions given by the ordered pair: $\bar{x}_i = (x_{i1},x_{i2}) = (\frac{c_i}{CD},\frac{b_i}{(BD)'})$ where $(BD)'$ is the effective bandwidth of a disk array of D disks suitably scaled to account for a required blocking probability, as discussed in Section 5.4. Also note that D is assumed to be constant for each array. Following this normalisation each object has requirements between 0 and 1 in both capacity and bandwidth dimensions (x_{i1} and x_{i2} respectively).

As a simple illustration of the poor performance of the FF algorithms, the following case is considered. Seventeen items are to be packed with a mean in each dimension of 0.16. The x-dimensions are all constant at 0.16 (implying that all movies are the same

length), while the y-dimensions are distributed according to the Zipf distribution with C=0.79 (resulting in the required mean size of 0.16). The lower bounding techniques produce a minimal requirement of three bins. Figure 5.6 illustrates the packing obtained by the FFGAR algorithm.

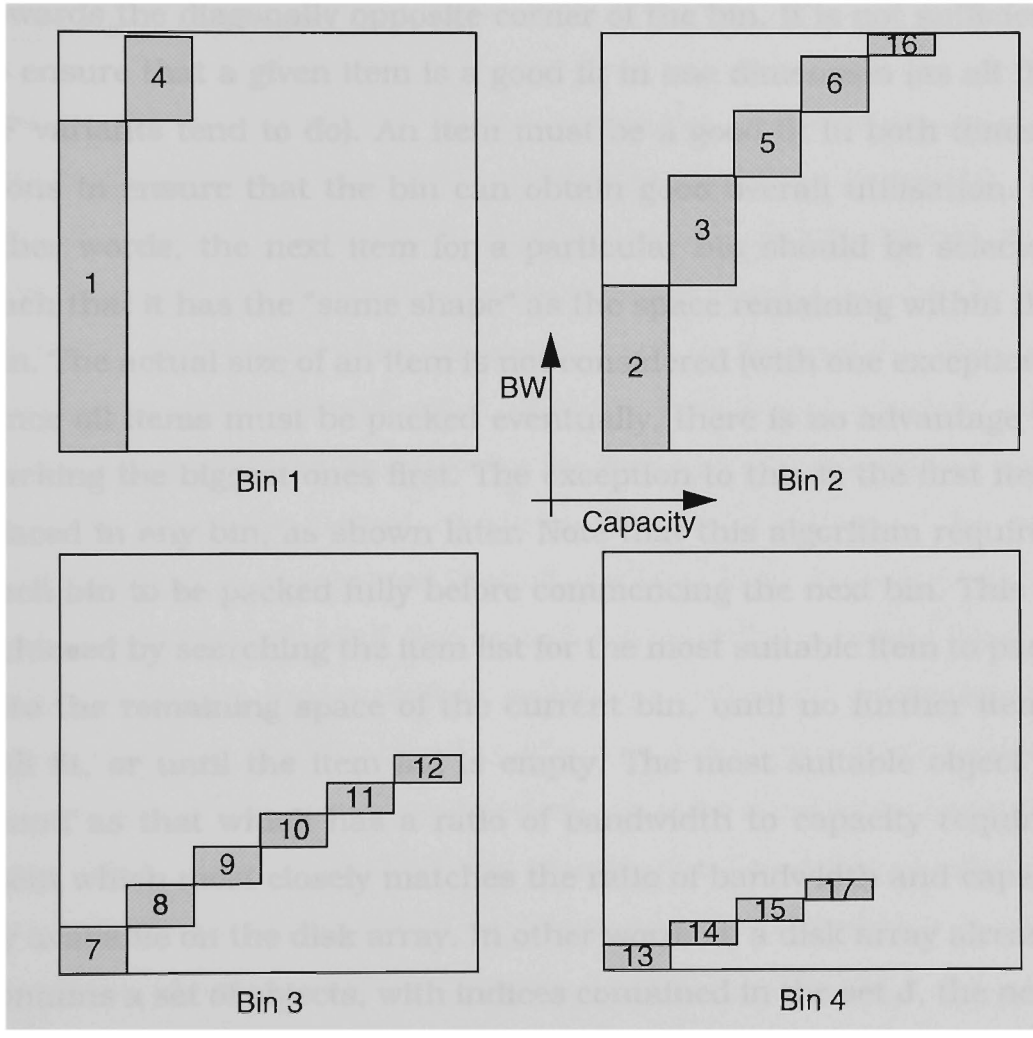


Figure 5.6 Example packing obtained by FFGAR algorithm

It is seen that the FFGAR algorithm requires 4 bins, an increase of 33% over the lower bound. While this in itself is not sufficient evidence that the packing can be improved, investigation of the actual packing obtained suggests that an improvement should be possible. From Figure 5.6 it is observed that bin 1 has a large wastage in the x-dimension (capacity), bin 2 is quite well packed, while bins 3 and 4 both waste the y-dimension (bandwidth) to a large degree. In order to gain an overall improvement in packing efficiency, it would seem

necessary to ensure that both capacity and bandwidth dimensions are utilised equally by each bin. It is this realisation that is employed in the Same-Shape-Biggest-First heuristic proposed here.

To ensure that both capacity and bandwidth are well utilised by each bin, it is necessary to pack items such that each item proceeds towards the diagonally opposite corner of the bin. It is not sufficient to ensure that a given item is a good fit in one dimension (as all the FF variants tend to do). An item must be a good fit in both dimensions to ensure that the bin can obtain good overall utilisation. In other words, the next item for a particular bin should be selected such that it has the "same shape" as the space remaining within the bin. The actual size of an item is not considered (with one exception), since all items must be packed eventually, there is no advantage to packing the biggest ones first. The exception to this is the first item placed in any bin, as shown later. Note that this algorithm requires each bin to be packed fully before commencing the next bin. This is achieved by searching the item list for the most suitable item to pack into the remaining space of the current bin, until no further items will fit, or until the item list is empty. The most suitable object is found as that which has a ratio of bandwidth to capacity requirement which most closely matches the ratio of bandwidth and capacity available on the disk array. In other words, if a disk array already contains a set of objects, with indices contained in the set **J**, the next object (index i) is chosen in order to minimise the expression in Equation 5.13 while obeying the constraint that the object must fit within the bin (Equation 5.14 and Equation 5.15). (Recall that x_{i1} and x_{i2} represent the normalised capacity and bandwidth requirements of object i, respectively).

$$\text{minimise } \text{diff}_i = \left(\frac{x_{i1}}{x_{i2}} - \frac{1 - \sum_{j \in J} x_{j1}}{1 - \sum_{j \in J} x_{j2}} \right) \qquad \text{(Eqn 5.13)}$$

$$x_{i1} + \sum_{j \in J} x_{j1} \leq 1 \qquad \text{(Eqn 5.14)}$$

$$x_{i2} + \sum_{j \in J} x_{j2} \leq 1 \qquad \text{(Eqn 5.15)}$$

Such a selection is made by traversing the list of remaining objects for each object to be packed. This heuristic is termed Same-Shape (SS). The requirement to traverse the item list for each selection results in a higher time-complexity for SS than the FF algorithms. This trade-off is discussed later.

Due to the heavily-skewed movie popularity distribution, popular objects have a large bandwidth requirement and do not match the "shape" (ratio of bandwidth to capacity) of the storage devices very well. This fact results in these objects being chosen last by the SS algorithm and hence often requiring a bin to themselves, creating wastage. A simple modification of this Same-Shape heuristic can alleviate this problem. By selecting the first one or more objects for a new bin to be the largest remaining object (in either of the two dimensions) it is guaranteed that all the large (and difficult to pack) objects won't be left until last and all be requiring separate bins. It should be noted that a similar motivation originally prompted the improvement to the FF algorithm of presorting objects in decreasing order of size (FFD), which has been shown to be a universal improvement. The adoption of this idea creates the Same-Shape-Biggest-First (SSBF) heuristic which, in the next section is shown to give considerably improved performance.

It will be seen (Figure 5.12) that selecting just the single largest object first for each bin generally results in the most efficient packing and the flowchart for this variant of the SSBF algorithm is shown in Figure 5.7.

It should be noted that object replication is required by the SSBF heuristic only if the disk array limitation (imposed by Equation 5.5) is too small to allow a popular movie to be stored on a single array due to its large bandwidth requirement. In this case the movie can

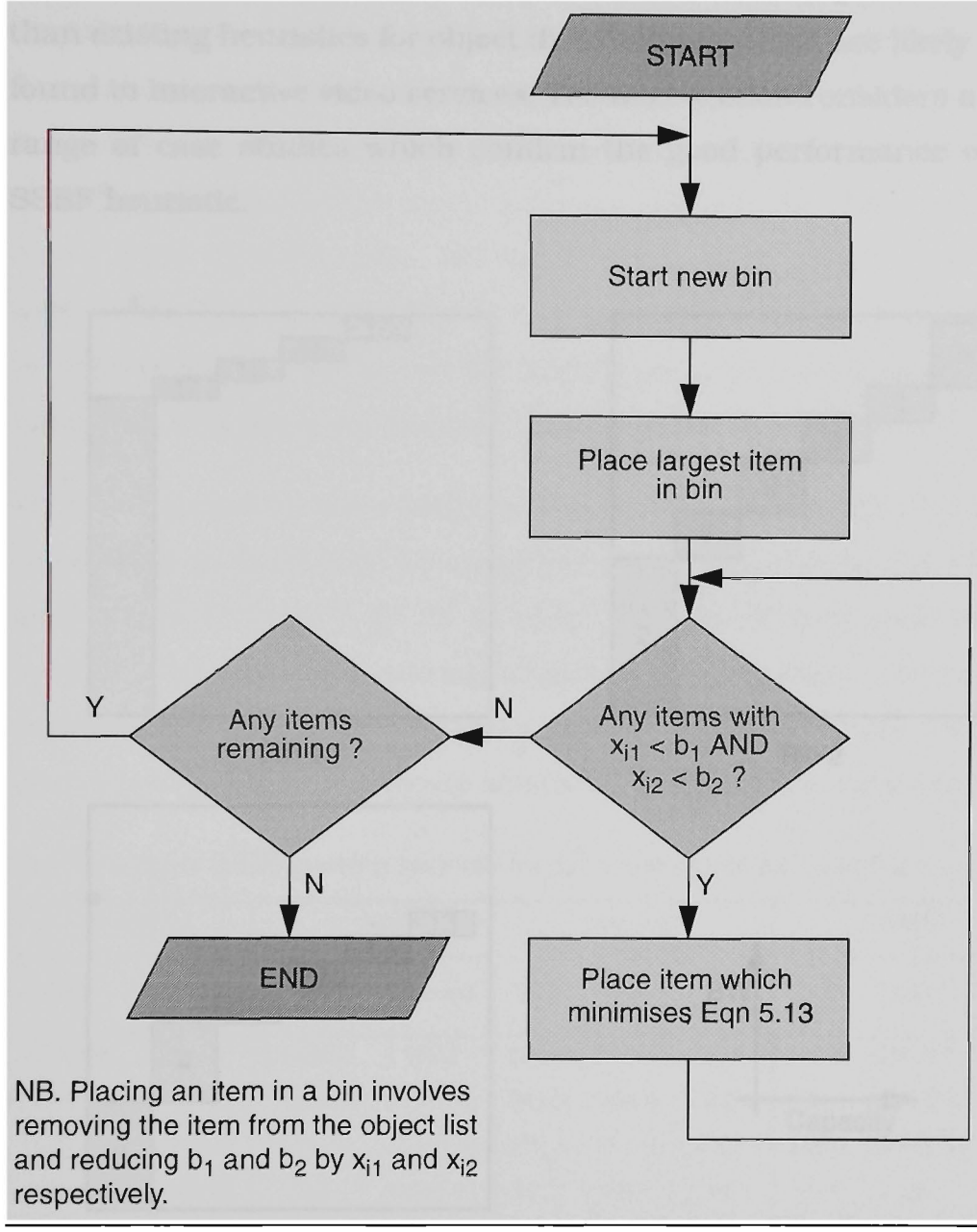


Figure 5.7 High-level flowchart of SSBF packing heuristic

be duplicated and treated as two separate objects with half the bandwidth requirement each. We consider this problem further in Chapter 7.

Revisiting the above example, Figure 5.8 shows the packing obtained by the SSBF heuristic for the same 17 objects. It can be clearly observed that all bins obtain better utilisation in both capacity and bandwidth dimensions and that the number of bins required is now equal to the lower bound of three, derived earlier. Although simplis-

tic, this example implies that the SSBF heuristic may perform better than existing heuristics for object distributions which are likely to be found in interactive video services. The next section considers a wide range of case studies which confirm the good performance of the SSBF heuristic.

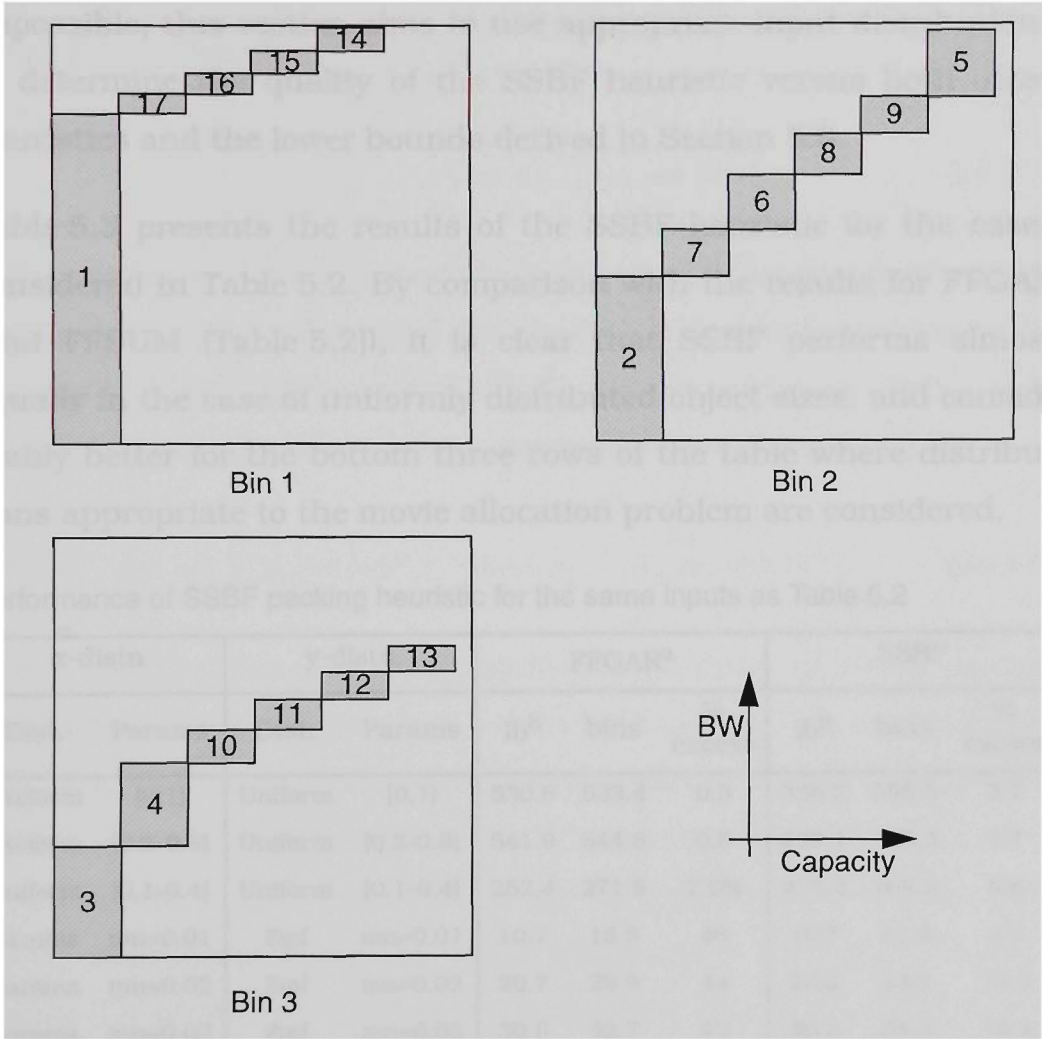


Figure 5.8 Improved packing performance of SSBF for example of Figure 5.6

5.8 Case Studies

This section uses a series of case studies to show that the performance of the SSBF heuristic is significantly better than those previously proposed, for the problem of allocating movies onto disk arrays. As has already been discussed, worst case analyses of packing heuristics tend to give a very poor indication of expected per-

formance in a typical situation. Also, previous average case (simulation) studies have not focused on the types of input distributions which are appropriate for the movie allocation problem. From Table 5.2 it is clear that algorithms which perform well with uniformly distributed object sizes, may not perform as well with other object size distributions. Although exhaustive comparisons are impossible, this section aims to use appropriate input distributions to determine the quality of the SSBF heuristic versus both other heuristics and the lower bounds derived in Section 5.6.

Table 5.3 presents the results of the SSBF heuristic for the cases considered in Table 5.2. By comparison with the results for FFGAR (and FFSUM (Table 5.2)), it is clear that SSBF performs almost equally in the case of uniformly distributed object sizes, and considerably better for the bottom three rows of the table where distributions appropriate to the movie allocation problem are considered.

Table 5.3 Performance of SSBF packing heuristic for the same inputs as Table 5.2

x-distn		y-distn		FFGAR[a]			SSBF		
Dist.	Params	Dist.	Params	lb[b]	bins	% excess	lb[b]	bins	% excess
Uniform	[0,1]	Uniform	[0,1]	530.6	533.4	0.5	536.2	555.8	3.7
Uniform	[0.2-0.8]	Uniform	[0.2-0.8]	541.9	544.8	0.5	539.1	548.3	1.7
Uniform	[0.1-0.4]	Uniform	[0.1-0.4]	252.4	271.5	7.6%	252.2	268.9	6.6
Gamma	mn=0.01	Zipf	mn=0.01	10.7	15.8	48	10.7	11.2	4.7
Gamma	mn=0.02	Zipf	mn=0.02	20.7	29.9	44	20.3	23.2	14.3
Gamma	mn=0.03	Zipf	mn=0.03	30.6	42.7	40	30.5	34.9	14.4

a. The values for FFGAR are the same as those in Table 5.2 and are reproduced here to allow easy comparison.
b. Note that the lower bounds shown are the greater of lb1 and lb2 as indicated by Equation 5.12. In rows 1 and 2 the tight lower bound was given by lb2 while in the remainder of the rows lb1 gave the tighter constraint.

Although promising, the results obtained by the SSBF algorithm warrant more detailed consideration. The motivation for the SSBF heuristic arose from the inability of previous heuristics to deal with steeply decaying long tailed distributions of object size as is expected in the movie allocation problem due to heavily skewed popularities.

The results presented above indicate that the SSBF heuristic does indeed cope well with this type of distribution, while maintaining adequate performance with the uniform distributions.

In order to confirm this conclusion the skewed distribution of [Maru77] has been employed. This distribution, denoted by G(2,m,a,b), is generated from m i.i.d. U(0,1) random variables according to Equation 5.16.

$$x = a\left(\prod_{i=1}^{m} y_i\right) + b \qquad \text{where } y_1, \ldots, y_m \text{ are U(0,1)} \qquad \textbf{(Eqn 5.16)}$$

This distribution has a range from b to a+b and the degree of skew is dictated by m. A bell-shaped distribution with similar properties is obtained by summing a set of U(0,1) random variables. This distribution, denoted by G(1,m,a,b) is generated from Equation 5.17.

$$x = a\left(\left(\sum_{i=1}^{m} y_i\right)/m\right) + b \qquad \text{where } y_1, \ldots, y_m \text{ are U(0,1)} \qquad \textbf{(Eqn 5.17)}$$

These distributions have the significant property of easily defined and bounded ranges (from b to a+b in both cases). This is in contrast with many of the more common distributions including the Zipf and Gamma distributions used to date. When using the Zipf and Gamma distributions it has been necessary to truncate the distribution, which depending upon the other parameters can effect results. Figure 5.9 shows the cumulative probability functions of G(1,m,1,0) and G(2,m,1,0) distributions for various values of m.

Before discussing further results obtained using these distributions, a second metric for evaluation of the quality of a packing is introduced. Results in Table 5.2 and Table 5.3 have shown the percentage excess required by a packing over the lower bound obtained. If lower bounds are tight, this is an effective measure of the wastage of the packing compared to the optimum packing [Coff84]. If however, the lower bounds are not tight, the results can be misleading. The percentage excess is also exaggerated when the number of bins is

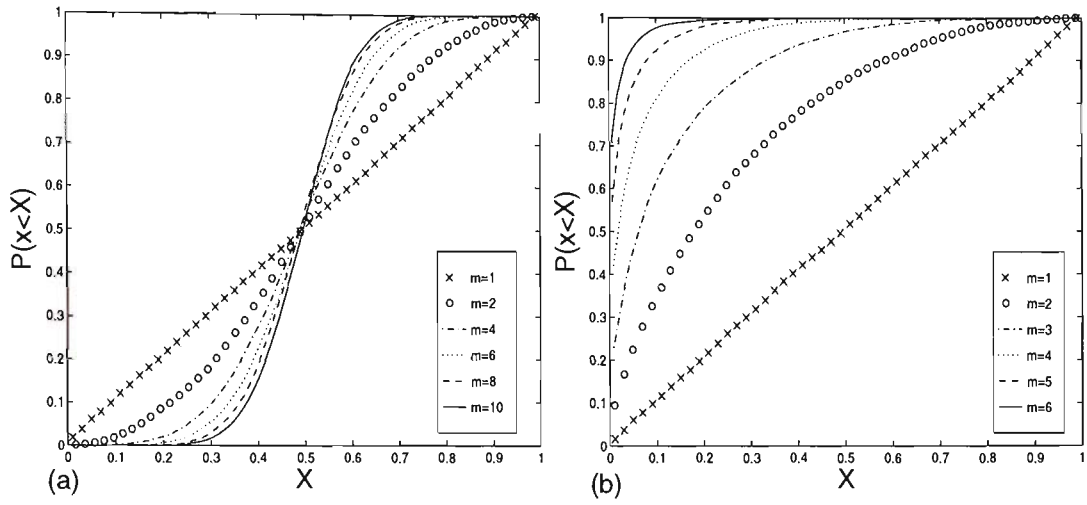


Figure 5.9 Cumulative probabilities for (a) G(1,m,1,0) and (b) G(2,m,1,0) distributions

small. As already seen in our example, an excess of 33% was obtained for the FFD heuristic even though the packing required only one bin in excess of the lower bound. A second measure (used in [Maru77]) is that of bin utilisation obtained by a packing. [Maru77] defines this as follows.

$$U_A = \frac{\max_j \left(\sum_{i=1}^{n} x_{ij} \right)}{\text{Containers Required}} \qquad \text{(Eqn 5.18)}$$

Note that this definition of utilisation only accounts for the dimension that has the highest utilisation, other dimensions may be poorly utilised if the totals are dissimilar. Since it is assured that the means of the object sizes are the same in all dimensions in all the cases considered here, this is not a significant issue. The utilisation measure is independent of lower bounds, and instead gives a measure of the fullness of the bins. As noted in [Maru77], however, a low value of U_A does not necessarily imply a poor packing algorithm. Indeed for certain object size distributions, [Maru77] states that even the optimal packing may approach a utilisation as low as 0.5. In such cases the percentage excess over the lower bound may be a more suitable measure of packing quality.

Figure 5.10 compares the performance of several heuristic packing procedures for a varying degree of skew in the popularity (y-dimensions) distribution. Increased skew is effectively modelled by increasing m in the G(2,m,a,b) distribution. The capacity requirement (x-dimension) of each object is selected from a G(1,6,a,0) distribution with a selected to ensure that the mean matches the mean requirement in the y-dimension. This ensures that the total requirement in each dimension is approximately equal and as such high utilisation is possible in both dimensions.

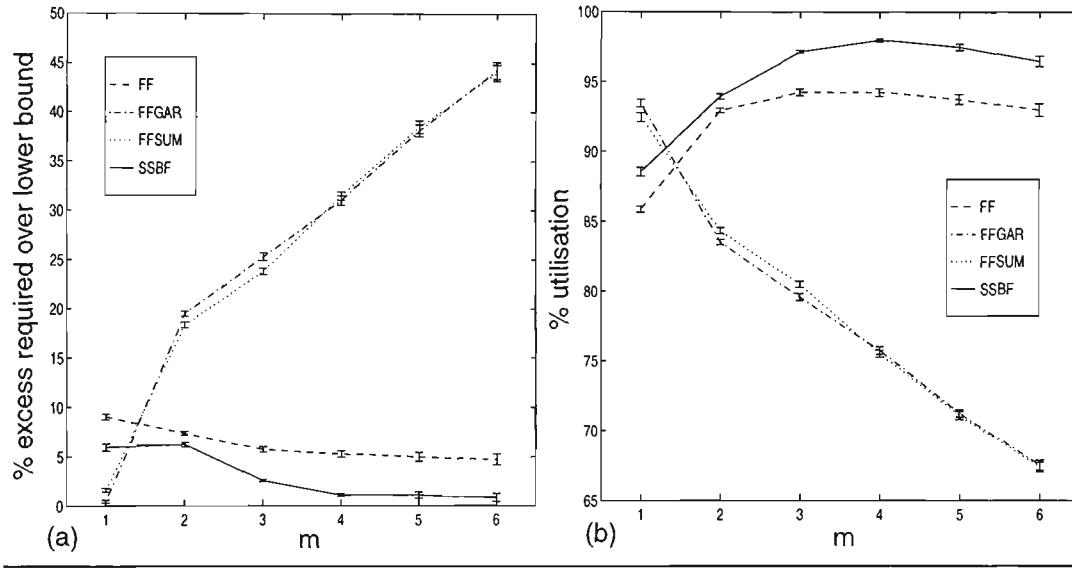


Figure 5.10 Excess required and utilisation achieved by various packing heuristics versus m for the G(2,m,1,0) distribution

Figure 5.10 (a) shows the percentage of bins required in excess of the requirement found by the greatest lower bound. This figure is calculated as a percentage relative to the lower bound and the points shown are the result of 100 independent simulation runs, packing 1000 objects each time. Figure 5.10 (b) shows the utilisation obtained by each packing as calculated by Equation 5.18 as a percentage. In all graphs the intervals shown are for 95% confidence.

The primary result from Figure 5.10 is that the SSBF heuristic proposed here provides the most efficient packing over a large range of values of m. The exception to this is when m=1 (ie. the y-dimension distribution is uniform), in which case the decreasing FF algorithms

(FFGAR and FFSUM) both perform extremely well. This agrees with results shown numerous times in the literature [Maru77].

The result for the standard FF heuristic is interesting. It is observed that as the skew of the y-distribution increases, this unsorted version of FF outperforms both of the sorted varieties. This implies that sorting the input list in the manner suggest by FFGAR and FFSUM is actually detrimental to performance of the FF heuristic for skewed distributions. It should be noted that FFGAR and FFSUM are the two most successful sorting heuristics for multidimensional vector packing from the literature ([Maru77] [Gare76] [Spie94]). The reason for this worsening performance as skew increases is implied by Figure 5.6 which illustrates the packing obtained by FFGAR for a small set of Zipf distributed objects. In that case popular objects are initially packed together, wasting capacity, and later unpopular objects are packed together, wasting bandwidth (see Figure 5.6). By leaving the objects unsorted, the randomisation assists the FF heuristic in gaining an efficient packing by mixing popular and unpopular objects.

Given the variable size of video servers (from FES's storing only 10's of movies to archival servers storing 1000's) it is important to consider the effect that the number of objects has on the packing efficiency obtainable. Figure 5.11 shows the performance of several heuristics versus the number of objects stored. The object size distributions used are G(1,6,0.125,0) for capacity and G(2,4,1,0) for bandwidth.

From Figure 5.11 (a) it is observed that the excess of the SSBF heuristic over the lower bound is consistently low and decreasing as the number of objects increases. The FF heuristic displays a similar trend, although at a consistently higher excess than that of SSBF.

Interestingly, the two sorted FF heuristics perform worse (in terms of both excess bins required and utilisation) as the number of objects increases. This can be explained in similar terms to the explanation

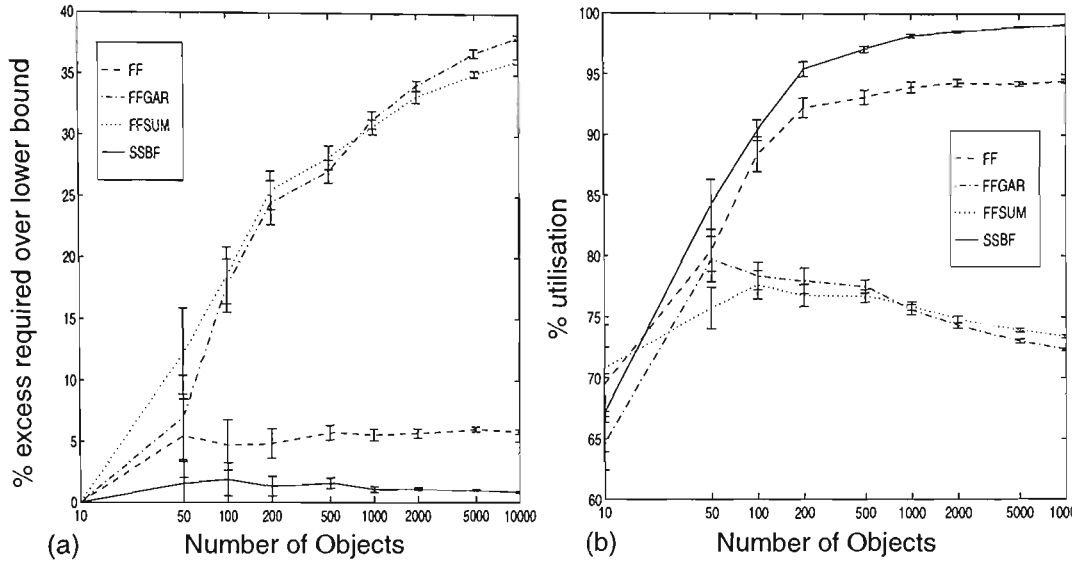


Figure 5.11 Excess required and utilisation achieved by various packing heuristics versus the number of objects packed

for Figure 5.6. As the number of objects increases, there will be a greater number of large objects and a much greater number of smaller objects due to the long tail of the heavily skewed popularity distribution. When these objects are sorted into some sort of decreasing order, the First-Fit heuristic will tend to pack just a few large objects together into a single bin, fully utilising the bandwidth dimension but underutilising capacity. Once the larger objects are depleted, the smaller objects will be packed, now fully utilising capacity but wasting bandwidth. This problem is not observed with the simpler unsorted FF heuristic since the random order of objects ensures that small and large objects are more likely to be packed together, giving a relatively good packing.

The results shown to date have used the SSBF algorithm with only the first object of each bin being selected as the largest remaining object (Biggest First). Figure 5.12 shows the percentage excess for cases where other numbers of objects are selected using the Biggest First method. The figures shown are for an object capacity distribution of G(1,6,0.25,0) and a bandwidth requirement distribution of G(2,3,1,0), with 1,000 objects to be packed in each case. The error bars are negligible (comparable with Figure 5.10) and are omitted for

clarity. It is clear that in this case the SSBF variant which selects a single object using the Biggest First criteria results in the most efficient packing. This observation remains true for the other input distributions investigated here. Note that as the number of objects selected as Biggest First increases, the efficiency approaches those of the FFGAR and FFSUM algorithms (see Figure 5.10 at the value of m=3). This is to be expected since the SSBF algorithm reverts to a form of FFD algorithm as the number of Biggest First objects increases.

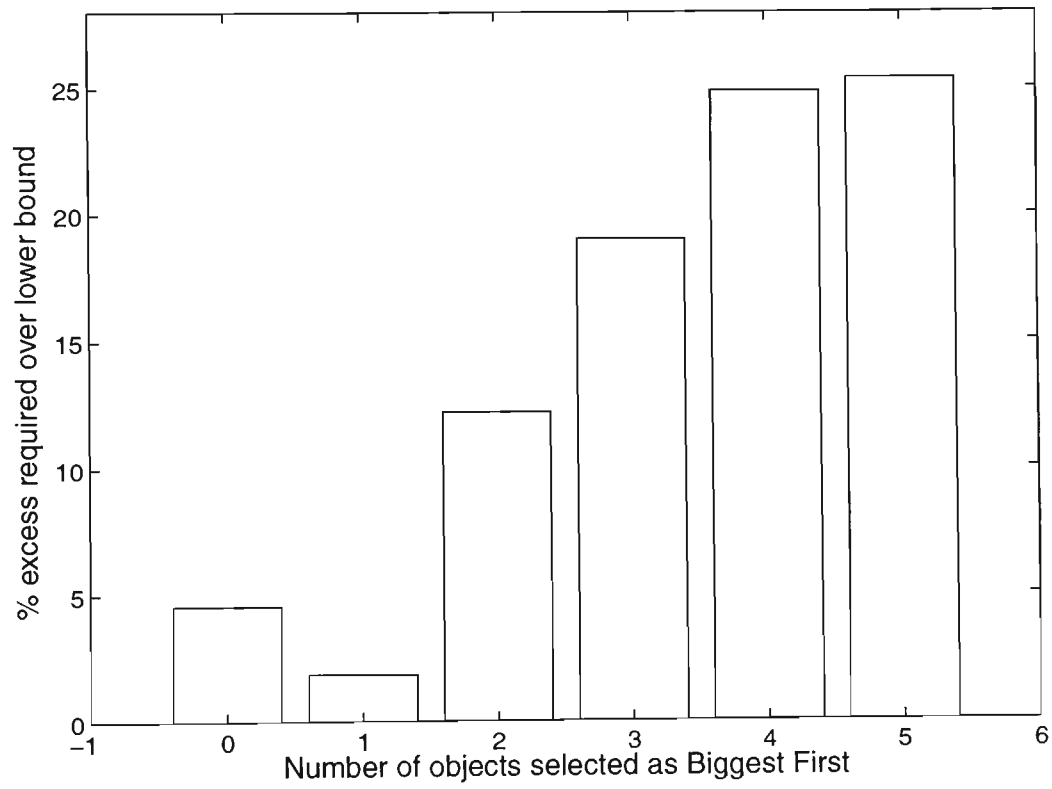


Figure 5.12 Comparison of packing efficiency versus number of objects selected as the biggest remaining objects

As already mentioned, the one penalty paid by the SSBF heuristic is its higher time complexity. In Figure 5.13 the execution time of each heuristic is shown against the number of objects packed. The values shown are CPU seconds of execution time on a Sparcstation IPX with each of the heuristics written in C.

The curves of Figure 5.13 reveal that the SSBF is indeed considerably more expensive than the other algorithms in terms of execution

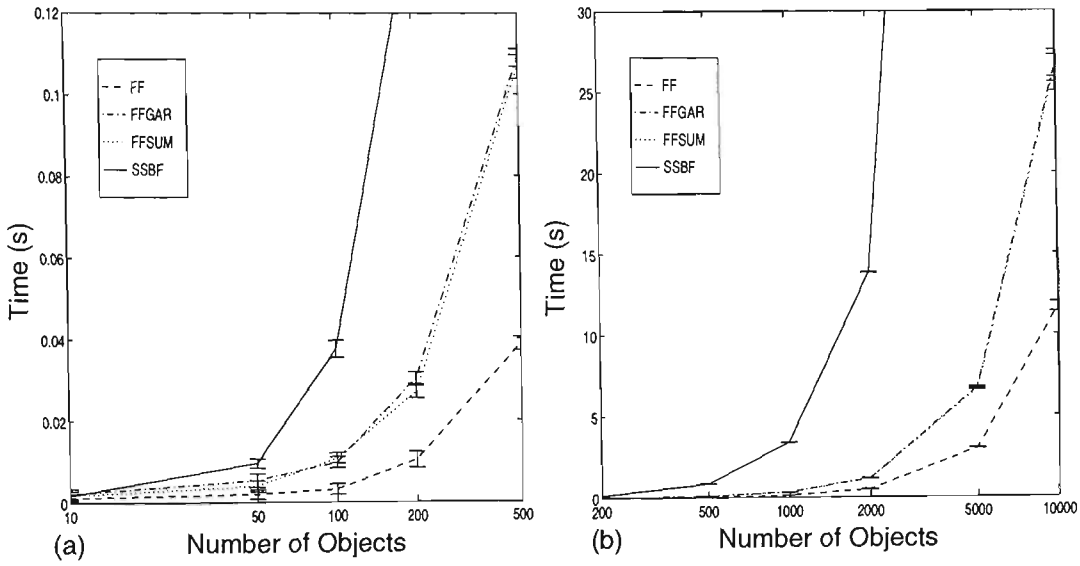


Figure 5.13 Execution time of various packing heuristics versus the number of objects packed.

time. However, the graphs shown can be misleading and the maximum execution time for the SSBF algorithm for 10,000 objects was actually only 360 seconds. In other words, the SSBF algorithm takes 6 minutes to run on the largest set of objects likely to be stored in a single video server. Given that the allocation of objects to disk arrays takes place on a timescale of days (or even weeks), this 6 minute overhead is insignificant. Recall also that using generally applicable heuristics (such as simulated annealing) can result in running times of many hours for cases with only tens of object being packed [Spie94].

It should be noted that the time complexity of the SSBF heuristic is easily determined to be $O(n^2)$. This is due to the fact that for each of the n objects the entire set of objects is traversed in order to find the best fit for the current available space in the array (see the flowchart in Figure 5.7). The measurements shown in Figure 5.13 reveal that the execution time of the SSBF algorithm is equal to $3.85 * n^2$ microseconds where n is the number of objects requiring packing. Further, the other heuristics do generally perform on the order of O(nlogn) as anticipated, with both FFGAR and FFSUM having identical execution times. This is expected since both involve sorting the

data set before applying the FF algorithm. FF itself is of course the fastest of all, since no sorting is required on the input dataset.

5.9 Conclusion

Utilising homogeneous disk arrays for video service overcomes the implementation problems of using hierarchical storage systems, of which heterogeneous disk arrays are one type. Previously it has not been clear that such homogeneous arrays will be capable of efficiently storing objects with widely varying capacity requirements and rapidly changing bandwidth requirements. An efficient packing scheme was required if such a goal was to be obtainable.

This chapter has presented an efficient heuristic for allocating objects to homogeneous disk arrays. An examination of the allocation problem revealed its similarity to the two-dimensional vector packing problem of operations research. This optimisation problem, known to be NP-hard, has previously been solved by the use of bin-packing heuristics such as First-Fit and First-Fit Decreasing. Although known to provide high quality solutions for uniformly distributed object sizes, these heuristics were shown to perform poorly for the types of object size distributions anticipated in interactive video servers. This fact combined with the poor performance and long execution times of generally applicable heuristics [Spie94], lead to the proposal of a new problem specific heuristic termed Same-Shape Biggest First.

Same Shape Biggest First (SSBF) utilises problem specific information to provide near optimal solutions for a range of appropriate object size distributions. Further, the SSBF heuristic is shown to provide solutions which are consistently close to the tight lower bounds also developed in this chapter.

This chapter has also shown that the Erlang-B formula can be used to accurately model the blocking probability of a disk array based

video server. This fact has then been applied to allow the raw bandwidth of a disk array to be scaled to give an "effective bandwidth" in terms of the number of streams that can be supported while still meeting a certain blocking probability constraint.

Although the architecture of the video server proposed in this chapter has changed somewhat from that assumed in the cost model of Chapter 3, it will be shown in Chapter 7 that the cost model in Chapter 3 and the argument in favour of distributing storage across the network still hold. Indeed the disk based nature of the server ensures that the cost model developed earlier is still fundamentally valid.

Following the object placement discussed above, a video server is able to commence serving requests as they arrive for the individual objects stored within each disk array. In order to ensure that QoS constraints are met, the server will need to implement a call-admission control (CAC) procedure before admitting new requests. Such a process is required to ensure that sufficient resources are available within the server to support the new request. In the next chapter a unique CAC scheme is proposed which is aimed at minimising admission delay and delay variation for new requests.

6. Call Admission Control for Disk Array Based Servers

Our patience will achieve more than our force.

- Edmund Burke

6.1 Introduction

This chapter presents a novel call-admission control scheme aimed at alleviating short term load imbalances across a disk array in an interactive video server. Such load imbalances increase admission delays and will be shown to occur frequently when using the simple admission schemes previously proposed. The scheme proposed here uses the semi-deterministic nature of disk array operation to make predictions regarding the future load on each disk in the array. By admitting clients onto a lightly loaded part of the array, the overall load can be better balanced and hence utilisation will be improved. Further, this scheme can be used to differentiate between admission and interactivity requests. It will be seen that an interactivity request can be treated as a call release and a re-admission to a different part of the array. Given the "interactive" nature of these requests it seems reasonable to suggest that they should be handled with lower delay than initial admission requests. With this in mind the two-priority scheme proposed here is able to delay admission requests to maintain a balanced load while also improving the response time to interactivity requests.

As was shown in Chapter 4, coarse-grained disk arrays in the nature of RAID 5 provide the most cost effective means of delivering large video objects to customers. One drawback of coarse-grained striping, however, is that the load on the individual disks is not inherently well balanced across the array. As mentioned in [Vin94b] the instantaneous load on each disk can vary dramatically from one service round to the next. This variation results in poor array utilisation, since lightly loaded disks are underutilised. [Vin94b] attempts to address the issue by allowing underutilised disks to continue reading extra data in a particular round and buffering this data until it is needed. The increase in array utilisation thus comes at a cost of a significant increase in buffering.

The metrics used to compare the simple and predictive CAC schemes presented in this chapter require careful consideration. One of the goals of the predictive scheme is to improve load balance across the entire array. As such, comparisons of the variance of the array load and minimum and maximum values of load between the two schemes would seem reasonable. Load balancing alone, however, is of no use if it does not provide some tangible benefit to the user. As will be shown, the benefit expected is in terms of the delay experienced by the user between issuing a call admission request, and the commencement of video playback. It is important to note that it is not only the mean value of this delay that it is important, but also the variability. Previous work in the field of computer-human interaction has shown that users will tolerate relatively long delays if this is what they expect, and if it is what they consistently receive [Shne84]. Obviously, reducing mean delay is desirable, but it is clear that a reduction in variance (or the upper percentiles) of delay may be more beneficial. For these reasons mean delay, variance and the upper percentiles of delay are used as the primary basis to evaluate the CAC scheme proposed here.

The remainder of the chapter is set out as follows. Section 6.2 reviews the salient points of the operation of coarse-grained disk

arrays for interactive video. Section 6.3 discusses the simple CAC scheme from existing literature. It is shown that this scheme can lead to load imbalance, which in turn effects viewer delay. This result motivates the requirement for the more efficient CAC scheme (termed predictive CAC) which is presented in Section 6.4. As part of this section, interactivity is discussed and it is shown how interactivity requests can be dealt with more efficiently than call admission requests. Section 6.5 presents a set of case studies comparing the simple and predictive CAC schemes for situations with varying degrees of user interaction. Following these case studies general conclusions are drawn regarding the properties of the predictive CAC scheme in Section 6.6.

6.2 Operation of Coarse-Grained Disk Arrays

Following the results of Chapter 4, this chapter limits itself to the consideration of coarse-grained disk arrays. As already discussed, in a coarse grained array, blocks of each video object are stored on individual disks in a round-robin layout[1]. During playback, as clients request sequential blocks of video in every cycle, the load on each disk moves in round-robin fashion from one disk to the next. This idea is illustrated in Figure 6.1 for a four disk array (ignoring parity) with two objects (A and B) each consisting of just 8 blocks.

Note that during initial allocation the first block of object A (block A0) was allocated to disk 1, while the first block of object B (B0) was placed on disk 3. There is no particular reason for this, except to indicate that all objects need not share the same starting disk. Assume that at some time (the start of cycle i) 8 customers were present in the system and cycle i required the retrieval of blocks A0, A4, A6, B1, B3, B4, B5 and B6 as indicated. Due to the sequential nature of video playback (assuming no interactions or terminations),

1. Note that the distributed parity blocks of RAID-5 architectures change this layout slightly, but by using Left-Symmetric data placement the round-robin nature is preserved. [Chen94b]

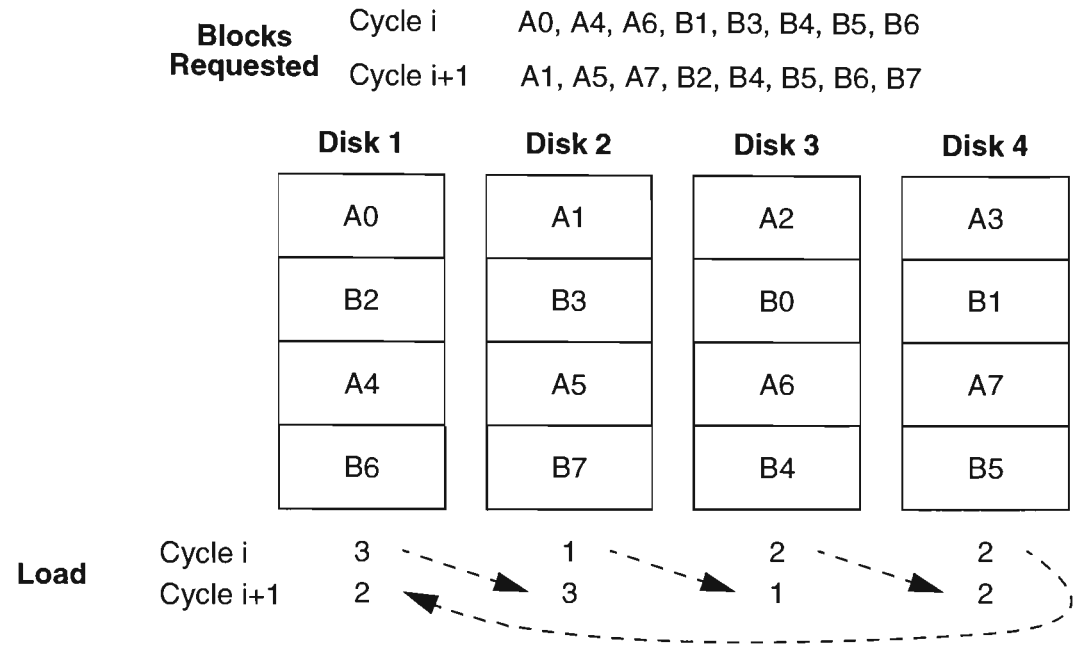


Figure 6.1 Operation of a coarse-grained disk array.

the blocks required during cycle i+1 will be A1, A5, A7, B2, B4, B5, B6 and B7 as shown. The effect that this has on the load on each disk is clear. The load is seen to move from one disk to the next in a cyclic fashion since in general a client being served by disk d_i in round i, will be served by disk $d_{i+1} = (d_i+1) \bmod N$ during round i+1.

As this load rotates around the disks, it is clear that in the long-term all disks will do an equal amount of work. As such it can be stated that the load on the array is balanced in the long-term. In the short-term however, it is possible that the load on individual disks will vary considerably across the array. The consequence of such variation will be an increase in call admission delay for particular requests if the desired start disk is fully loaded, even if other disks are only lightly loaded.

Figure 6.2 shows an (admittedly contrived) example, again assuming a 4 disk array, where each disk can serve a maximum of 10 streams. In part (a) of the figure, the load is very unevenly spread, leading to a very high delay for the new request. In part (b) the same load is now

evenly spread across all disks and the new request can be admitted at the end of the current cycle.

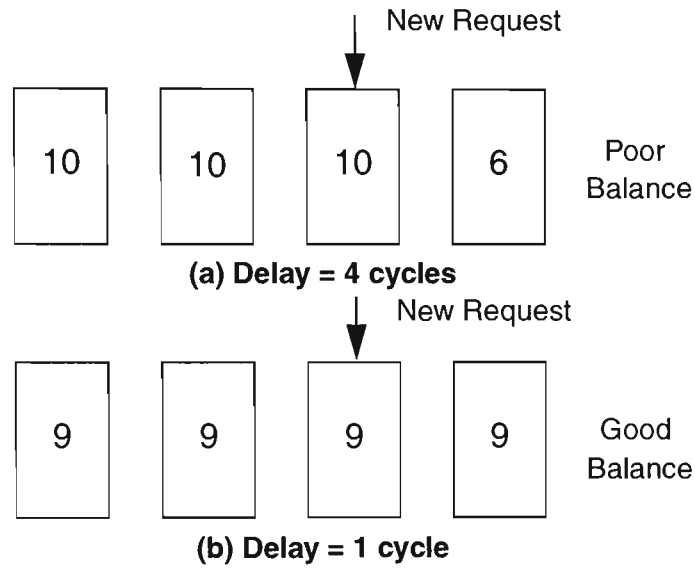


Figure 6.2 Delay incurred by (a) a poorly balanced system, versus (b) a well balanced system

The next section discusses the simple CAC scheme and demonstrates the poor load balance achieved by this scheme.

6.3 Simple CAC Scheme

In a coarse-grained array each disk has a predetermined upper limit on the number of streams that can be served concurrently. In other words, if the number of streams currently being served by that disk is less than this upper limit, then a new stream can be admitted. As discussed in Chapter 2, the effort to date has been focused on methods for determining this upper limit (see for example [Chan94b] and [Vin94a]). Previously proposed "simple" CAC schemes (which although not often discussed explicitly are implied in the literature including those references cited above), typically admit a new stream to the required disk in the array whenever possible. If the current disk is fully loaded, the request may be queued until the load on the required disk has decreased to the point that a new stream can be admitted, or until the waiting client reneges and leaves the system.

Such a simple scheme relies on the independence of individual requests to ensure that during steady-state operation, the load on the server is relatively well balanced. Unfortunately, despite the independence of each request, it is possible that the load may become quite significantly unbalanced. In other words certain disks may be fully loaded while others remain lightly loaded. This in turn effects user admission delay as indicated in Figure 6.2.

Before developing a new CAC scheme, it must first be determined how poorly balanced a system is likely to be when employing the simple CAC policy. To investigate the severity of the likely load imbalance, an approximate queuing model is used. Each disk in the array can be modelled as a multiserver queue with independent Poisson arrivals. Further it is assumed that requests arriving at fully occupied queues are blocked and leave the system (ie. there is no queueing). Also, since it has already been shown in Chapter 5 that results for M/M/m/m queues tend to hold well for M/G/m/m queues it is assumed that call holding times are Poisson. Now given a system utilisation of $\rho = \lambda / \mu$ the probabilities of state of an individual disk are easily calculated from [Klei75]:

$$p_k = \frac{(\lambda/\mu)^k}{k!} \Big/ \left(\sum_{i=0}^{m} \frac{(\lambda/\mu)^i}{i!} \right) \qquad \text{(Eqn 6.1)}$$

where p_k is the probability of k servers being occupied in an M/M/m/m queue (ie. the probability that a given disk is serving k streams at any moment). This distribution of p_k alone gives an indication of the likely load imbalance of the system. Figure 6.3 shows the distribution of p_k for a disk capable of serving 10 streams and utilisations ranging from 0.7 to 0.9.

The curves in Figure 6.3 represent the probability of a particular number of streams being served by a given disk in the array. The high variance of the distribution indicates that despite high average loads on the server there is a strong likelihood that a particular disk will only be lightly loaded while other disks in the array may be very

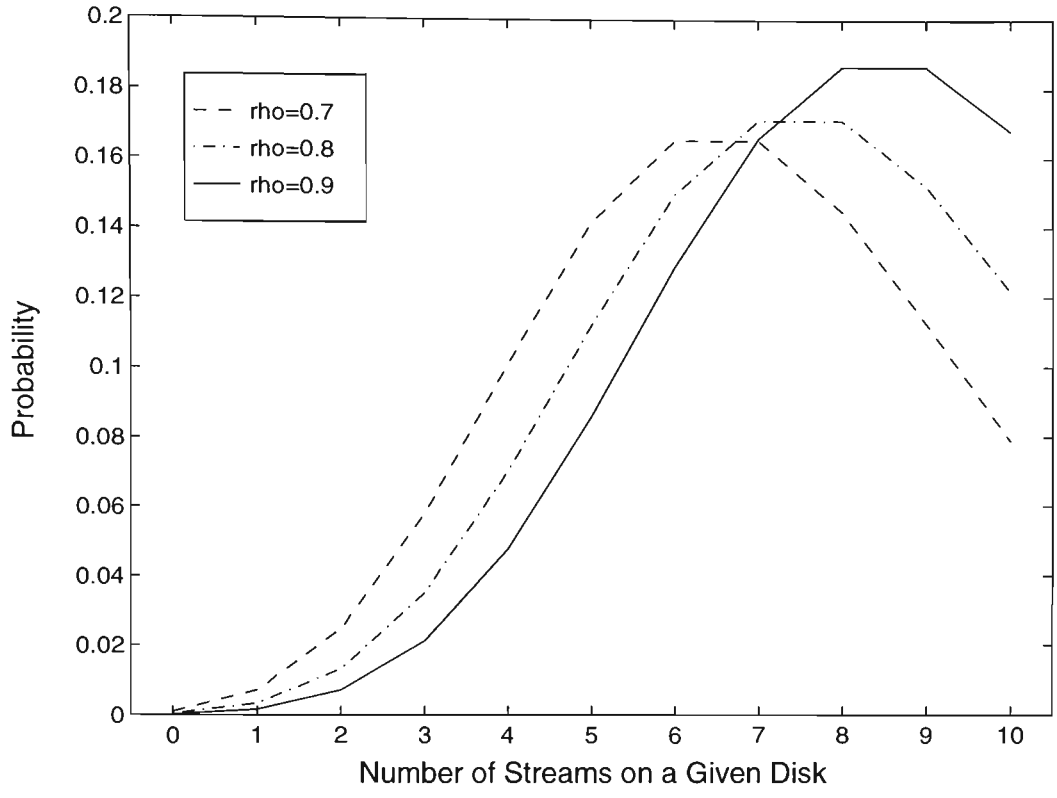


Figure 6.3 Distribution of number of active streams under a load of 0.7-0.9 for a single disk capable of serving 10 streams and no queueing.

heavily loaded, especially considering that a single array will consist of tens of disks.

To give further insight into the inherent load imbalance on a coarse grained disk array, consider the expectation of the minimum or maximum load on any disk in the array. In an array of N disks it is straightforward to calculate the probability that at least one disk will carry a particular load.

$$p_k^1 = \text{Prob[at least one disk has load k]} = 1 - [1 - p_k]^N \qquad \text{k=0,...,m} \qquad \textbf{(Eqn 6.2)}$$

From this it is possible to calculate the probability that k is the smallest number of streams being served by any disk in the array. Given independence between disks, the probability that a given load is the lowest in the array is calculated as follows:

$$p_k^L = \text{Prob[k is the lowest load in the array]} = p_k^1 \prod_{i=0}^{k-1} (1 - p_i^1) \qquad \textbf{(Eqn 6.3)}$$

Since for k to be the minimum load, loads of k-1, k-2,..., 0 must not occur. The probability that a given load (k) is the highest in the array can be determined similarly:

$$p_k^H = \text{Prob[k is the highest load in the array]} = p_k^1 \prod_{i=k+1}^{m} (1 - p_i^1) \qquad \text{(Eqn 6.4)}$$

Now, letting L denote the random variable of the minimum load in the array at any time, the expectation of L is easily calculated in the standard manner.

$$\begin{aligned} E[L] &= \sum_{l=0}^{m} l p_l^L \\ &= \sum_{l=0}^{m} \left[l p_l^1 \prod_{i=0}^{l-1} (1 - p_i^1) \right] \end{aligned} \qquad \text{(Eqn 6.5)}$$

and the expectation for the maximum load in the array at any time, denoted by H, can be found as follows:

$$\begin{aligned} E[H] &= \sum_{l=0}^{m} l p_l^H \\ &= \sum_{l=0}^{m} \left[l p_l^1 \prod_{i=k+1}^{m} (1 - p_i^1) \right] \end{aligned} \qquad \text{(Eqn 6.6)}$$

As shown in Figure 6.4, the difference between the expected minimum and maximum loads on the array is quite considerable, even in small arrays. Note that the graph also shows simulated results which are in total agreement with the analytic results from Equation 6.5 and Equation 6.6 above. The simulation model used is discussed next. This measure of load imbalance implies that there is significant room for improvement over the simple admission policy discussed so far.

In order to further investigate this load imbalance problem, an event-driven simulation has been developed. This simulation models the cyclic movement of load around the array, and admits and releases new customers according to the simple CAC scheme described above. The trace shown in Figure 6.5 (a) illustrates the

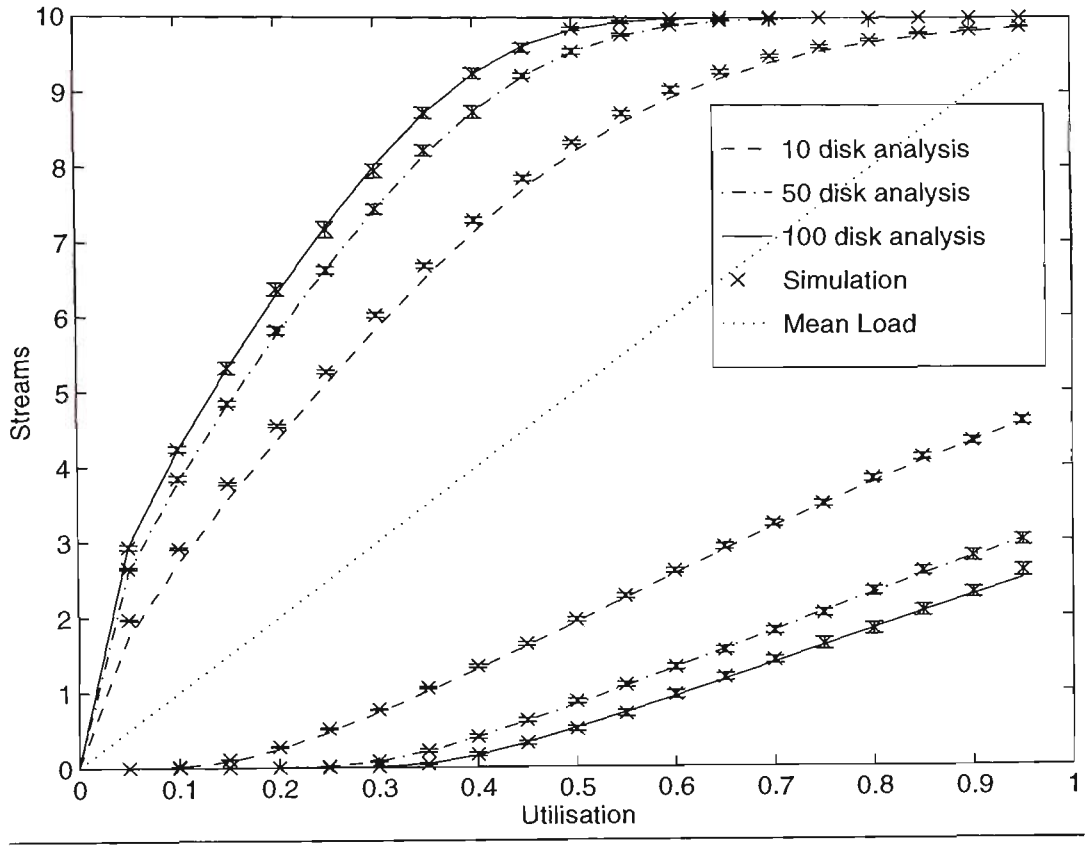


Figure 6.4 Expected minimum and maximum loads on various size arrays for a range of utilisations

delay experienced by each new request and the statistics of the load on the system at the time each request is accepted. For this figure, for example, the server is assumed to consist of 100 disks with each disk able to serve 10 streams in each cycle. The arrival rate of new requests is set to give an average utilisation of 0.9, with the interarrival time between requests being Poisson distributed.

Figure 6.5 (a) indicates the highly variable delay seen by new requests. The first 500 (or so) requests all receive a delay of less than 1 second (one cycle time) since the server is empty at the start of the simulation and this transient period sees disks becoming loaded. As soon as some of the disks are fully loaded, some requests will be delayed when they require a disk that is currently fully loaded. As load continues to increase (see Figure 6.5 (b)) until approximately the 900th request arrives, the delay seen by new requests continues to increase. The remainder of Figure 6.5 (a) reveals the high variabil-

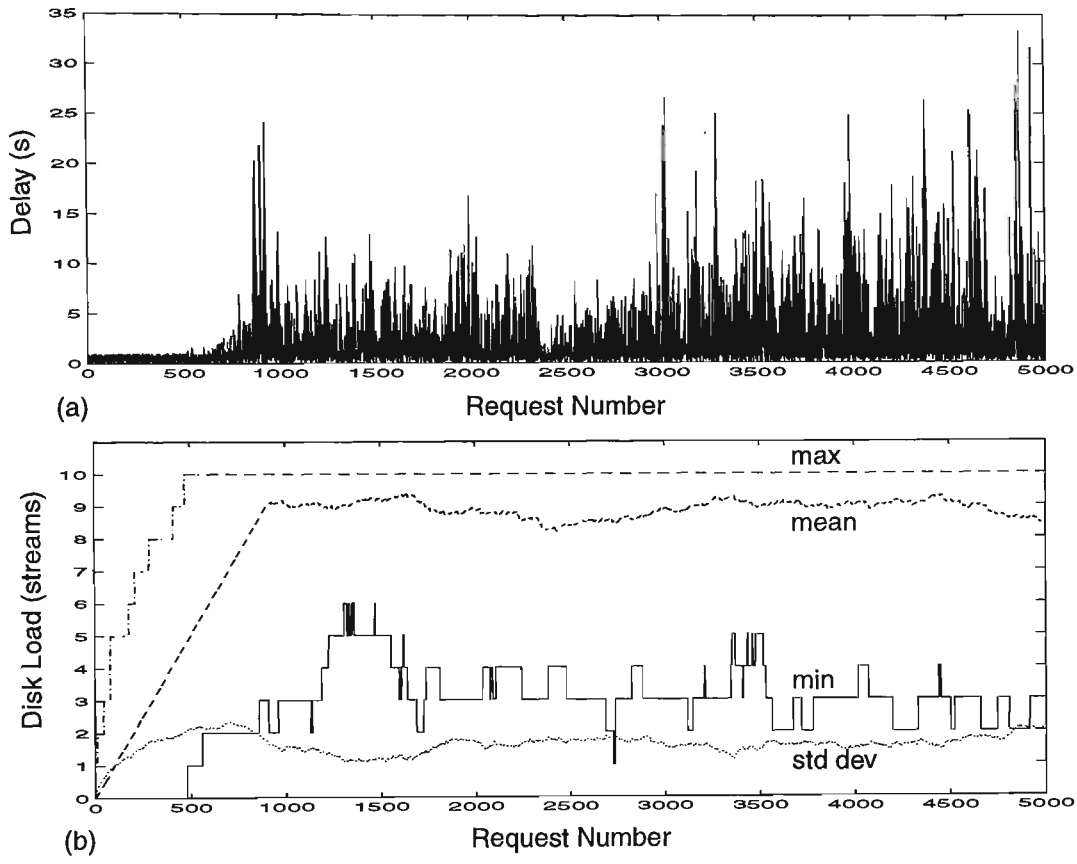


Figure 6.5 Delay and load for the Simple CAC scheme

ity of call admission delay with some requests being delayed for over 30 seconds before admission.

The plots in Figure 6.5 (b) reveal the cause of this delay variability. Ignoring the transient start-up period, there are always some disks fully loaded. With a utilisation of 0.9 this is to be expected. But the load on the least loaded disk at any time (represented by the solid line) is actually quite low (the mean value is just 3.22 streams on the least loaded disk[2]). This reinforces the result that load balance in the system is poor even when requests are queued. While many disks are fully loaded, a number are operating at loads of just 3 or 4 streams. The dotted line represents the standard deviation of the load.

2. Note that this differs from the result in Figure 6.4, since queueing is now incorporated into the simulation model.

A perfectly balanced system would (of course) have a deviation of zero and the maximum, minimum and mean values would all be identical at all times. Due to the integer nature of the number of streams on a disk this is clearly impossible, but a significant improvement should be possible over that seen in Figure 6.5 (b). The predictive CAC scheme introduced next, is aimed at achieving some improvement in the load-balance and hence delay characteristics of the coarse-grained disk array based video server.

6.4 Predictive CAC Scheme

It was demonstrated in Figure 6.1 that the load on a disk array passes from one disk to the next in a cyclic fashion at well defined intervals of time. As such, the load on a given disk can be predicted for long periods into the future with a high degree of accuracy. This accuracy is not complete, as calls terminate and new calls commence, changing the load on the disks. Due to the rapid cycling of load from one disk to the next, however, the predictions tend to remain very accurate. This accuracy comes about because load cycles on intervals around 1 second while changes in total array load (call arrivals or departures) occur on timescales of minutes. This point will be discussed further later, with respect to interactivity considerations.

It is the deterministic aspect of disk array operation that is used to advantage by the predictive CAC scheme. Given that our aim is to improve load balance within the array, the following framework is used. It is possible to view placing a stream on a lightly loaded disk as a *benefit*. That is, it is beneficial to the overall array performance and to future admission delays, to admit the current request to a lightly loaded disk. This benefit can be obtained at a *cost* of possibly delaying the admission of the current request. The predictive CAC scheme quantifies these costs and benefits and trades them off against each other to determine when a given call should be admit-

ted. Figure 6.6, illustrates the idea of delaying a new request in order to improve load balance.

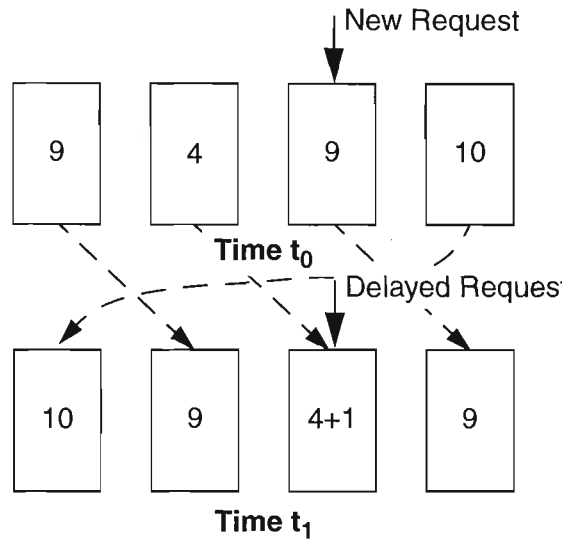


Figure 6.6 Delaying a new request by one cycle to improve load balance

At time t_0 a new request arrives requiring to start on disk 3 which currently carries a load of 9 streams. The simple CAC scheme would immediately admit this stream, resulting in a full load on disk 3. Investigating the load on the other disks in the array, it is observed that the load on disk 2 is just 4 streams and in the next cycle (at time t_1) this load will be transferred to disk 3. The predictive CAC scheme would determine that there is a large benefit associated with delaying the stream for just one cycle (small cost) to place it on a disk that is much less loaded. In other words the slight increase in delay for this request should be balanced by avoiding long delays for future requests. Note, however, that it is important to account for how long the current request has already been waiting when deciding whether to further delay it. The algorithm used by the predictive scheme is illustrated by the pseudocode of Figure 6.7.

In the algorithm, Mean_Load is the average load on all disks and Threshold is a parameter which determines when the algorithm becomes active. While Mean_Load is below Threshold the system relies on the simple scheme to maintain sufficiently good load balance. When the load climbs above the Threshold we use predictive

```
if (Mean_Load > Threshold)
    i = Request_Disk();
    j = (i + 1) mod N;
    while (j ≠ i)
        benefit = δ1 * (Streams(i) - Streams(j));
        cost= ((Delay(j)-Delay(i)) / Mean_Delay());
        if (benefit > cost)
            Delay_Request(j);
            exit loop;
        end /* if */
        j = (j + 1) mod N;
    end /* while */
end /* if */
```

Figure 6.7 Predictive CAC algorithm

CAC to improve the load balance. For the experiments performed here, the Threshold is set to 70% of the maximum load (unless otherwise stated). Without a threshold the scheme can be shown to incur unnecessary delay to new requests in a lightly loaded system.

δ_1 is a parameter discussed later. Request_Disk() returns the disk number used by the new request. Streams(i) returns the number of streams being served by disk i, and Delay(i) returns the delay until we reach disk i. Mean_Delay() uses a sliding window to determine the current mean delay experienced by requests into the system. Delay_Request(j) causes the current request to be delayed until the load currently on disk j has moved to the target disk.

As can be seen from the algorithm, the *benefit* of delaying a stream increases with the difference in load between the initial target disk and the prospective target disk. For example, if the target disk is very heavily loaded and a disk elsewhere in the array is lightly loaded, the benefit in delaying the stream until the light load is on our target disk, is high. The *cost* of delaying a stream is related to what increase in delay is incurred by doing so. As such, if the lightly loaded disk referred to above is a large "distance" away, this trans-

lates to a long delay and as such a high cost[3]. δ_1 is used as a weighting factor between the benefit and cost (with δ_1=0, the predictive scheme reduces to the simple CAC scheme, while when $\delta_1 \rightarrow \infty$, the predictive scheme would always provide perfect load balance at the cost of very long delays for admission). The Delay_Request(j) function will delay admission of the current request until the load currently on disk j is on the target disk.

The graphs shown in Figure 6.8 below reveal the advantage yielded by the predictive scheme. The trace used to generate these results is identical to that used for Figure 6.5 for the simple CAC scheme. In this case a value of δ_1=1.6 has been used. This value has been determined by experimentation. A rigorous scheme for determining optimum values of δ_1 requires further investigation.

Comparing Figure 6.8 with Figure 6.5 it is observed visually that the variation in delay is significantly reduced by the predictive scheme. Also, the load balance has been considerably improved with the least loaded disk now carrying an average of 6.01 streams. This improvement in load balance is also reflected by the decrease in the standard deviation of load, and it can be concluded that it is the improved load balance that leads to the lower variance in admission delay.

In Table 6.1 the metrics discussed in Section 6.1 are presented for the simple and predictive CAC schemes. The error values give 95% confidence intervals in each case.

Table 6.1 Various measures of delay of new requests for simple and predictive CAC schemes

	Mean	Variance	95th Percentile	99th Percentile
Simple CAC	3.3±0.2	27.5±9.5	12.3±1.0	22.6±2.2
Predictive CAC	2.95±0.2	13.5±2.5	9.2±0.7	17.3±1.6

3. Note that the cost is currently linearly related to distance. Although other relationships have been examined (eg. cost increasing as the square of the distance) they do not seem to have significant effect. This aspect of the predictive admission scheme does, however, warrant further consideration.

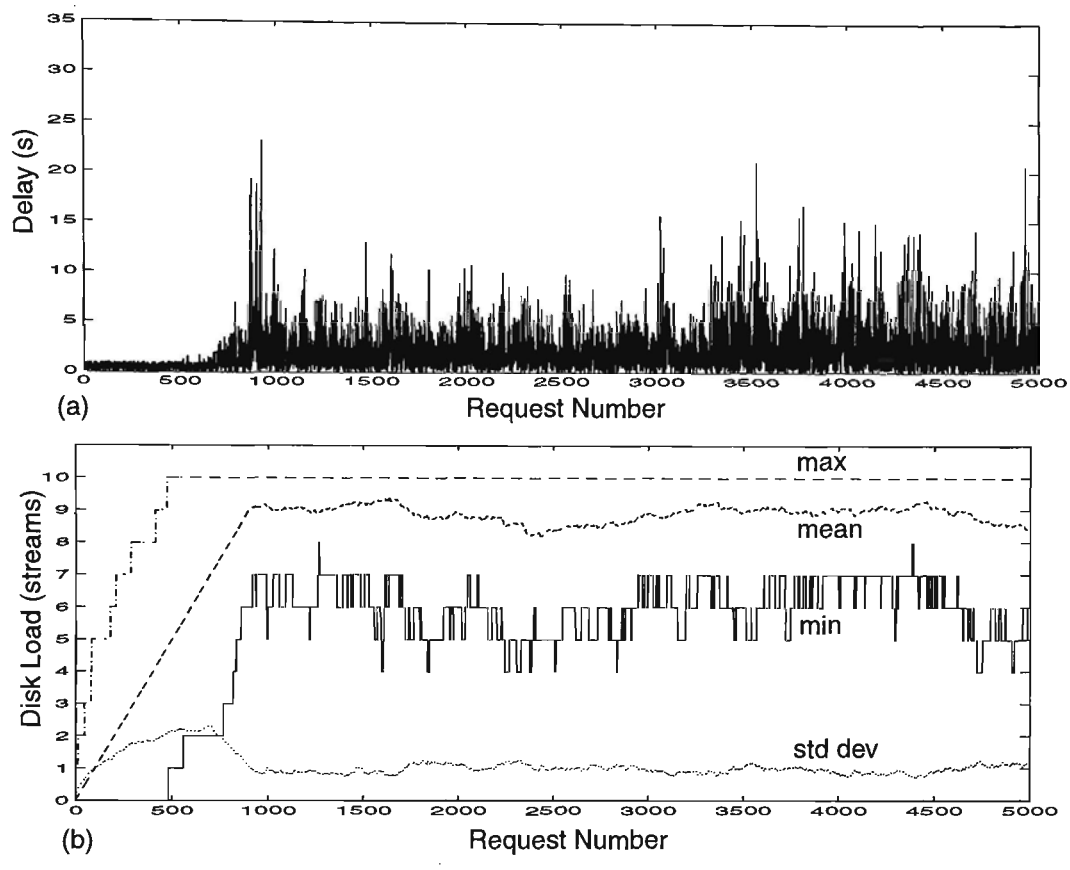


Figure 6.8 Delay and load for the Predictive CAC scheme

It is noted from Table 6.1 that the predictive scheme provides an advantage over the simple scheme in all metrics. The mean delay is only slightly reduced, but as already mentioned it is the upper percentiles of delay that tend to give a better indication of user satisfaction. From the 95th percentile figures it can be seen that the predictive scheme provides 25% lower delay than the simple scheme. Considering that this advantage is achieved at zero cost in terms of additional resources, it would appear that the predictive scheme is indeed worthwhile. Further comparisons are presented in Section 6.5.

6.4.1 Interactivity Considerations

The initial comparisons presented above have been carried out under the assumption that no interactivity takes place. This has the effect that the deterministic nature of disk array operation is only

disturbed by the arrival of new requests and the departure of completed requests. When a user interacts with the server the load on a number of disks may be effected. This will reduce the accuracy of future load predictions, which, in turn will effect the efficacy of the predictive admission scheme.

As discussed in Chapter 2, viewer interactivity can take a number of forms. Pausing, rewinding, fast and slow play are all types of interaction that may be supported in a video server. Each type of interaction may have a different effect on the server and on the individual disks in an array. Pausing, for example, temporarily reduces the load on the current target disk by one stream, increasing it later when the user resumes viewing. Fast play, on the other hand, can be implemented in a number of ways (see Section 2.4.5) with the effect on the disk array depending on the implementation. Given the uncertainty concerning which interactive functions will be required, and how they will be implemented, a simplifying (but realistic) assumption has been made in this section. It is assumed that all interactions have the same effect on the disk array. The effect is that of reducing the load on the current disk by one stream and increasing the load on some other (randomly chosen) disk by one stream. In other words the stream's current access point is moved to some new randomly chosen disk in the array. At some later time the stream is again moved in a similar manner, emulating the end of the period of interaction. This idea follows the model used in [Mour96] and effectively models servers which either encode separate streams for fast-play, reverse-play and the like [Saka96], or which support these functions via buffers in the STB [Alme96].

Using the above model, an interactivity request can be treated as a call release and a new call admission (with reduced residual service time) to a different part of the array. From the users perspective, however, it is likely that the user will expect more rapid response to an interactivity request than to a new call admission request. The nature of the predictive CAC scheme allows the system designer to

arbitrarily differentiate between admission and interactivity requests. While admission requests are admitted according the standard predictive scheme, interactivity requests can be handled with decreased delay by reducing the load balancing requirements, and admitting them with a lower values of δ.

Figure 6.9 is a block diagram of the operation of a video server employing predictive CAC for new requests and interactivity requests. Once a request reaches the server it can be identified as an admission or interactivity type request. From this point the admission requests are passed to the predictive CAC scheme (with parameter δ_1), which uses state information from the disk array to determine when to admit the stream to the required disk. The interactive requests generate a release message to the disk array and then use another invocation of the predictive CAC (with a different parameter value, δ_2) scheme to recommence with the new stream as soon as possible. Note that δ_1 and δ_2 represent different values of the same parameter used in different invocations of the predictive CAC scheme (see Figure 6.7) for admission and interactivity requests respectively.

Having already illustrated the potential benefits of the predictive CAC scheme in a video server without interactivity, it is now clear that the predictive CAC scheme has a potential further advantage in systems which do support interactivity. That is, the predictive scheme can be used with a high value of δ_1 to maintain load balance while simultaneously admitting interactivity requests as soon as possible by setting a lower value of δ_2. This has the desirable result that interactivity requests may be handled with shorter delays than the more delay tolerant admission requests [Alme96]. Note, however, that the support of interactivity can be expected to result in a reduction of the admission delay benefits seen earlier for the predictive scheme. This trade-off is illustrated in Section 6.5.

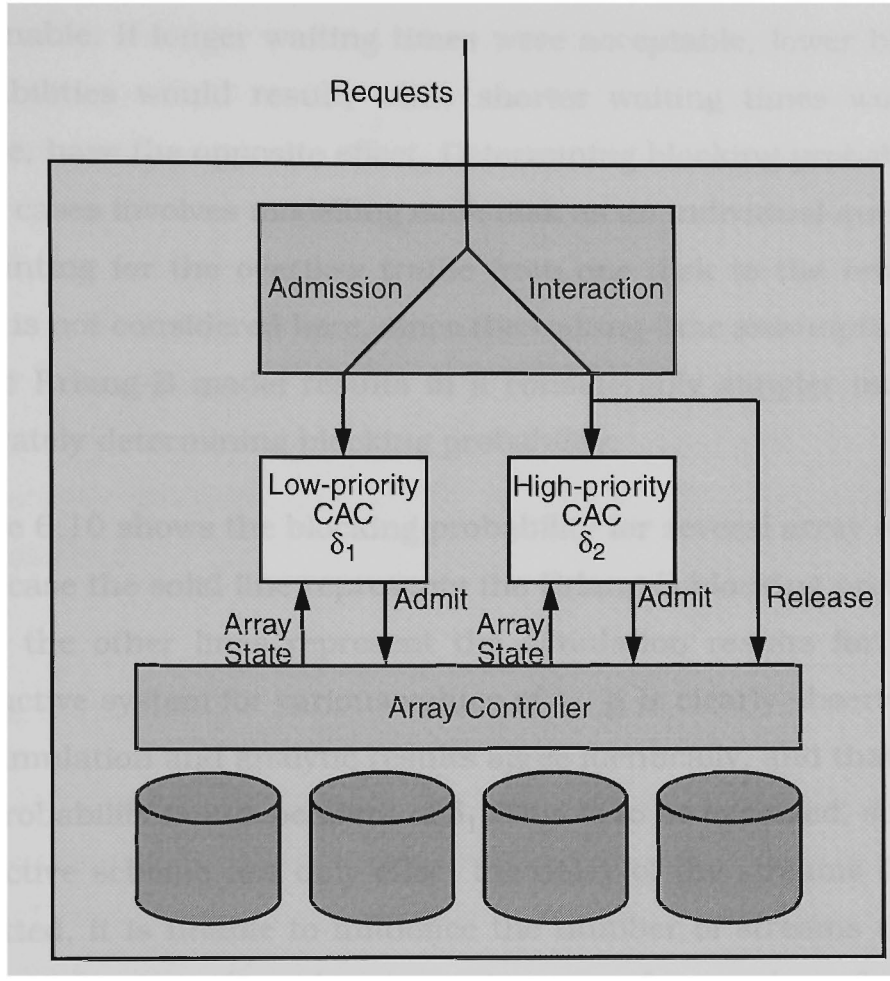


Figure 6.9 The operation of the predictive CAC scheme for admission and interactivity requests within a disk array based server

6.4.2 Blocking Probability

Before considering the delay performance of the predictive admission scheme in more detail, we first demonstrate that the blocking probability of the predictive CAC scheme is still accurately modelled by the Erlang B formula as discussed in Chapter 5. It has already been shown that an M/G/m/m queue can be accurately modelled by an M/M/m/m queue for moderate values of m (Section 5.4). For this model to be accurate in the case of an array with many disks, however, a customer must be willing to wait for one full service round before service commences. This constraint allows the array to be modelled as one queue with the number of servers, m, equal to the product of the number of disks and the number of streams admitted to each disk. Given that customers are likely to be willing to wait some finite amount of time, the constraint of one cycle time seems

reasonable. If longer waiting times were acceptable, lower blocking probabilities would result; while shorter waiting times would, of course, have the opposite effect. Determining blocking probability in these cases involves modelling each disk as an individual queue and accounting for the overflow traffic from one disk to the next. This issue is not considered here, since the waiting time assumption used in the Erlang-B model results in a considerably simpler model for accurately determining blocking probability.

Figure 6.10 shows the blocking probability for several array sizes. In each case the solid line represents the Erlang-B blocking probability while the other lines represent the simulation results for a non-interactive system for various values of δ_1. It is clearly observed that the simulation and analytic results agree identically, and that blocking probability is independent of δ_1. This is to be expected, since the predictive scheme can only effect the delay of the streams that are admitted, it is unable to influence the number of streams that the server can admit. No scheme can increase the number of streams admitted without increasing resources in some way.

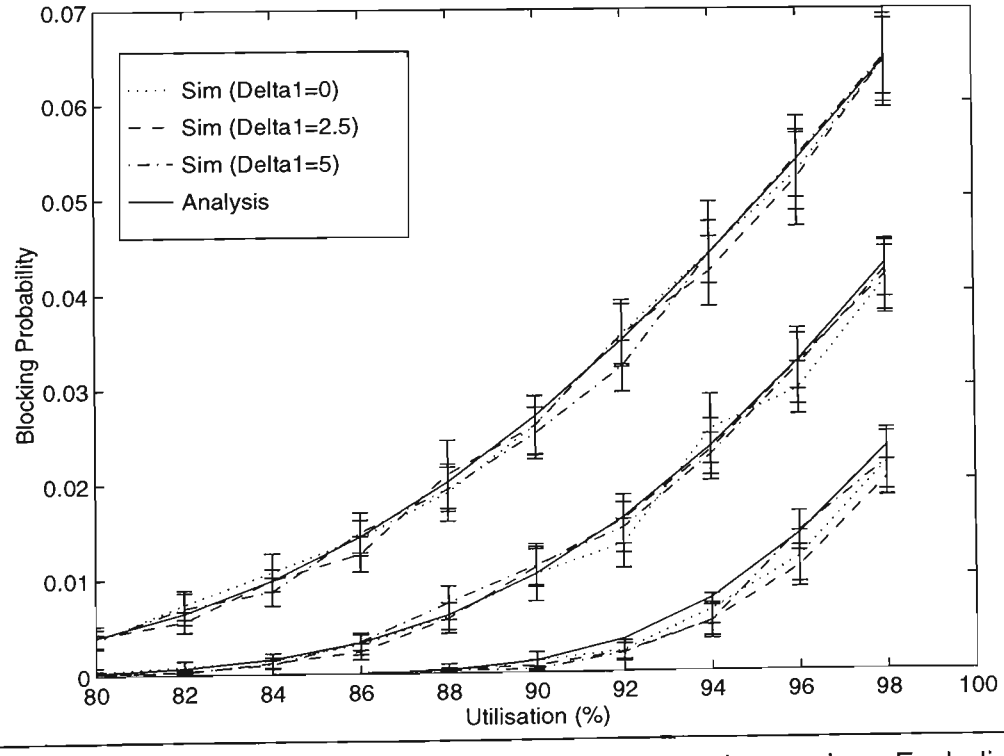


Figure 6.10 Blocking probability versus utilisation for several array sizes. Each disk serves 10 streams.

Although not explicitly shown, the level of interactivity has no effect on blocking probability. Since each interactivity request results in a decremented load on one disk and an incremented load on another, overall array load is unchanged and so blocking probability is not affected. It is clear that for the delay tolerance assumptions made here, the Erlang-B formula provides a very accurate and simple model for blocking probability of a disk array based video server. This model is independent of the CAC scheme used and the degree of interactivity (provided interactivity is modelled as a call release and readmission).

6.5 Case Studies

The case studies presented here are divided into two categories. The first set of results examine the comparative performance of the simple and predictive CAC schemes under the assumption of no interactivity using the metrics defined in Section 6.1. The second set of results are derived for situations where interactivity is permitted. In these cases interactivity is modelled as discussed in Section 6.4.1.

Unless otherwise stated the results shown here are for a single array consisting of 100 disks, with each disk capable of maintaining 10 streams. Each cycle lasts for one second, so load is passed from one disk to the next deterministically at the end of each second. The threshold for activation of the predictive scheme is set to 70% of peak load. The array is generally loaded to a utilisation of 0.9, and all error-bars represent 95% confidence intervals calculated using the method of batch means [Law91].

6.5.1 No Interactivity

Following the survey by Shneiderman ([Shne84]) it is clear that consistency of delay is an important factor in viewer satisfaction. Consistency of delay can be represented by the distribution of call admission delay. As such, the first item of interest when comparing

the predictive and simple CAC schemes is the cumulative frequency of delay which is presented in Figure 6.11 for a value of δ_1=1.6.

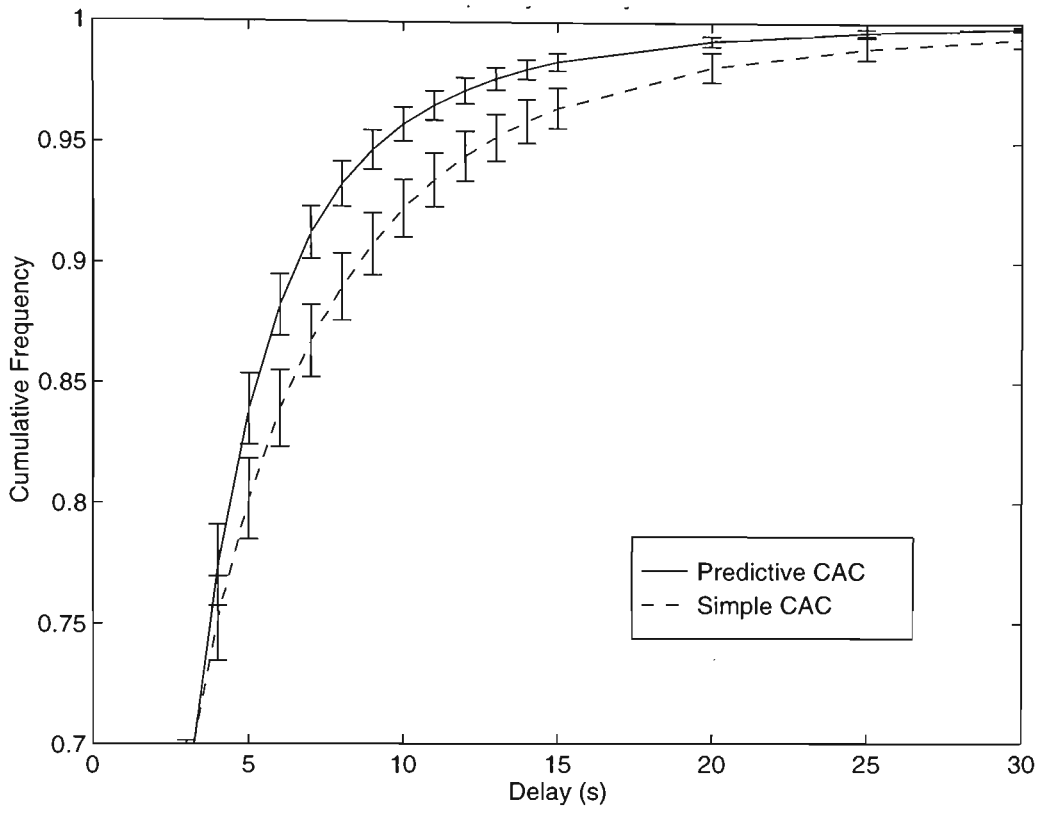


Figure 6.11 Cumulative frequency of delay for predictive and simple CAC schemes

If the system were able to provide a perfectly constant admission delay, the cumulative frequency would appear as a unit step located at the mean delay. Due to the fixed duration of service rounds a totally fixed delay is, however, impossible. The best that is possible is a delay that is constant to within the time of 1 service round (1 second in this case). It is observed from Figure 6.11 that the predictive scheme more closely approximates the ideal unit step than does the simple scheme. It should be noted that the improvement provided by the predictive scheme is also manifested in the upper percentiles of delay as shown in Table 6.1.

Another important consideration when dealing with the predictive scheme is how its performance is affected by the load on the system. For the next comparison, the same array was subjected to a load varying from 60% to 95% utilisation for each of the CAC schemes.

The 95th percentiles of delay for each scheme are shown in Figure 6.12.

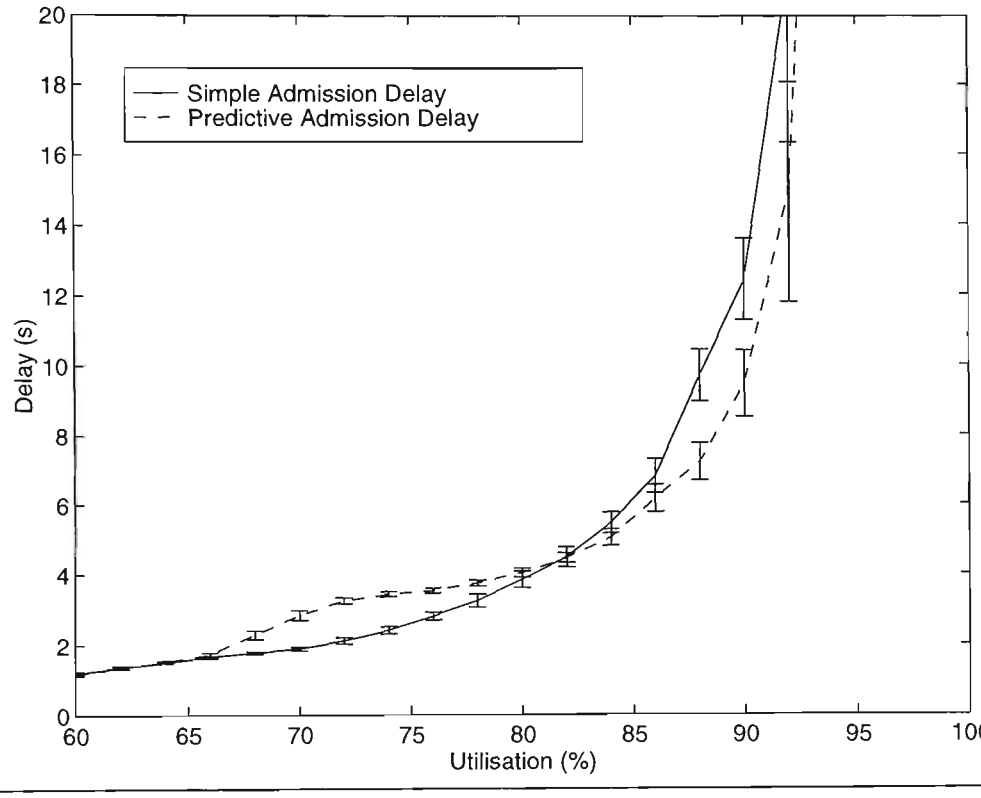


Figure 6.12 95th percentile of delay versus array utilisation for each scheme

It is observed from the figure that at high loads, the delay of the predictive scheme is significantly less than the simple admission scheme. Note, however, that at lower loads (70-80%) the predictive scheme actually incurs a higher delay than the simple scheme. This deviation in the dashed line is caused by the threshold of the predictive algorithm (see Figure 6.7) which is set to 70% of peak load. As the load on the system fluctuates around 70% the predictive scheme alternates between active and inactive states, causing increased delays to some requests, but does not effectively improve the system load balance. Below the threshold, both schemes operate identically, providing very small delays to all requests. It is clear from Figure 6.12 that the predictive scheme provides the most substantial benefits at high loads when delay can become a significant problem. It is for these situations that the proposed scheme has been optimised. At lower loads such a predictive scheme would not be

required. It is also for this reason that the threshold for the predictive algorithm has been set to 70% of the peak load for all the cases considered here.

From these results it is clear that a significant benefit can be provided by the predictive call admission control scheme in situations where interactivity is not allowed and predictions are made with a high degree of accuracy. As already discussed, interactivity will perturb the accuracy of load prediction, but will also allow different admission constraints to be supported for admission and interactivity requests. The performance of the predictive admission scheme in interactive video servers is considered next.

6.5.2 Interactivity Delay

In this section we make the assumption that interactivity requests should be given a higher priority than admission requests. That is, they should be admitted as soon as possible, whereas admission requests may be queued for longer periods. The model of Figure 6.9 is used in the cases presented here.

One important input parameter is the frequency of user interaction. It is clear that the amount of interaction is closely related to the content of the video (educational material, for example, has been found to be highly interactive [Bran96]). For the cases considered here we initially assume an entertainment style video-on-demand application. From an informal survey of movie-style video viewers we have chosen an initial figure of 25% interactivity. This figure implies that a quarter of all viewers will (on average) interact (FF/REW, pause etc.) once during a movie. Sensitivity of the scheme to this assumption will be discussed later.

As has already been discussed, the values of δ_1 input into the predictive CAC algorithm significantly affects the performance of the scheme. In the case where interactive requests are being separately admitted via a second instance of the predictive CAC (with a different

value of δ_2), the effect becomes somewhat different. Figure 6.13 shows the delay of admission and interactivity requests versus δ_1 (and for a range of values of δ_2) for the same server parameters as above. Note that mean values are shown, but 95th percentiles display almost identical trends.

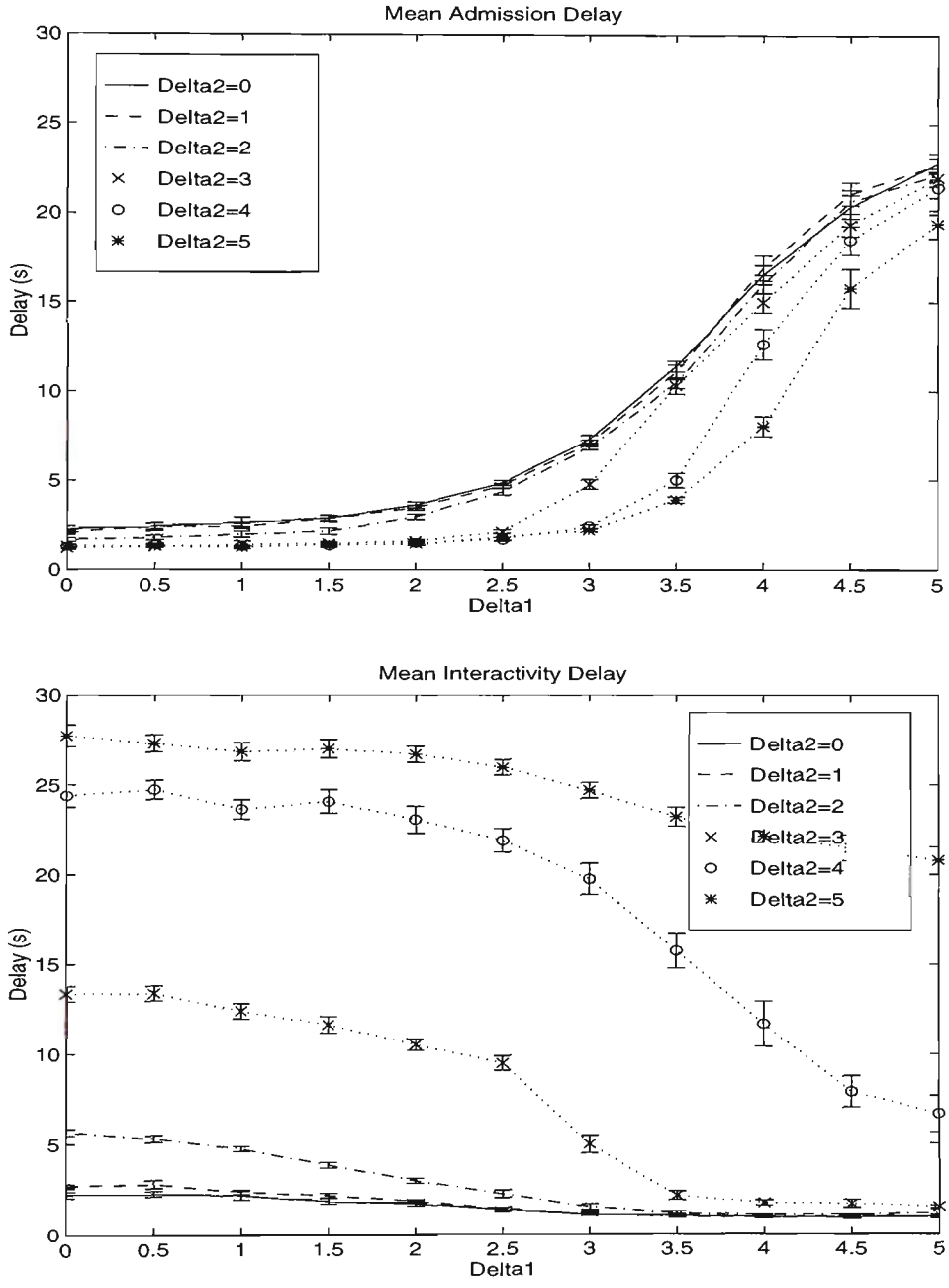


Figure 6.13 Mean admission and interactivity delays for various values of utilisation and a range of values of δ_1 and δ_2

The general observation from the figure is that as δ_1 increases, admission delay increases, while interactivity delay decreases. This

can be explained as follows. Small values of δ_1 reduce the perceived *benefit* of delaying a call admission request. As such, when δ_1=0, the predictive scheme reverts to the simple CAC scheme for admission requests. As δ_1 increases, the likelihood of delaying a call admission request to improve load balance increases. At the right hand edge of the graphs, load balance is essentially perfect at all times, at the cost of significantly higher admission delays. This perfect load balance does, however, have the desirable consequence that interactivity requests can now be handled with minimum delay.

From the graphs it is also clear that δ_2 has the opposite effect to δ_1. In other words, for low values of δ_2, interactivity delay is minimised while high values minimise admission delay. Note, however, that increasing δ_2 generally increases interactivity delay more than it decreases admission delay. This is due primarily to the fact that there are fewer interactivity requests than admission requests. For this reason, we consider cases where δ_2=0 for the remainder of the case studies presented here. This is chosen because it minimises interactivity delay at a cost of only slightly higher admission delay. It should be noted that for a given set of system requirements the choice of δ_2 must be investigated as δ_2=0 may not be optimal.

Fixing δ_2=0, it is clear that a system designer is able to vary the δ_1 parameter in order to trade admission delay against interactivity delay. Low values of δ_1 minimise admission delays at a cost of higher interactivity delays, while high values of δ_1 have the opposite effect. Selecting the appropriate value of δ_1 will depend on customer requirements, the content of the video being served, the degree of interactivity and the load on the system. Consideration of some of these factors is presented in a case study in Chapter 7. In the following studies, a value of δ_1=2.5 is selected as a reasonable trade-off of admission delay versus interactivity delay. This gives a decrease in interactivity delay for only a modest increase in admission delay as shown in Figure 6.13.

Next we consider how these delays vary with system load. The curves of Figure 6.14 show the 95th percentile of admission and interactivity delay for the predictive scheme as well as the same delays for the simple admission scheme. Note that the delays for admissions and interactions are identical under the simple scheme since both are admitted as soon as possible.

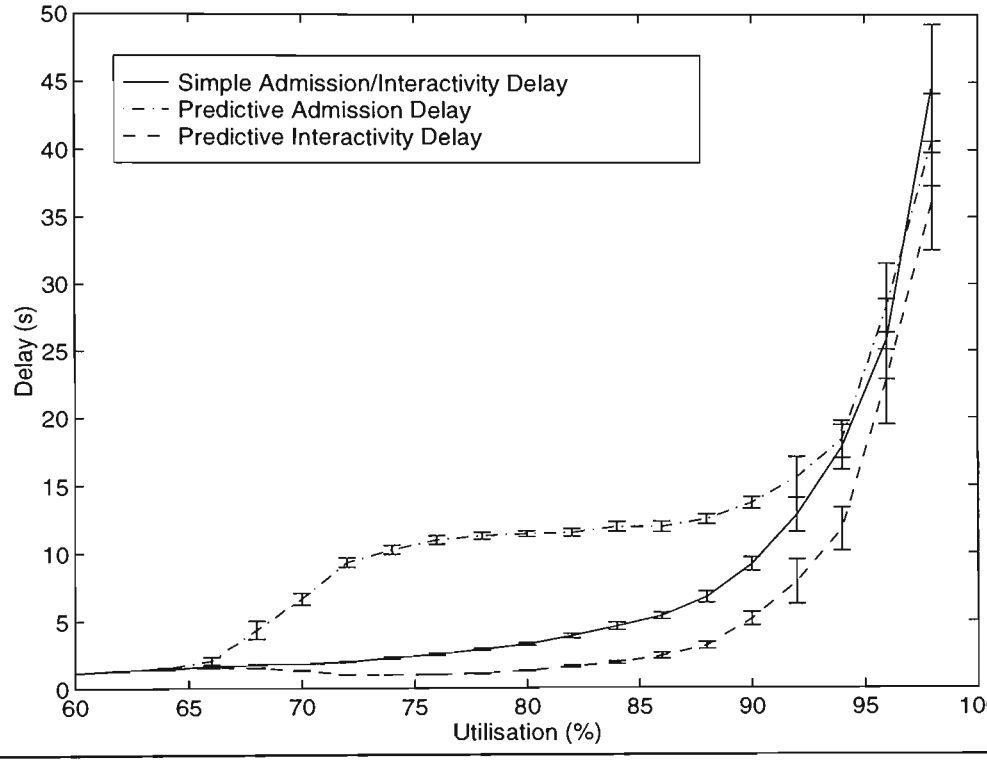


Figure 6.14 95th percentile admission and interactivity delays for simple and predictive admission schemes (δ_1=2.5, δ_2=0)

The results shown in Figure 6.14 are very encouraging. It is observed that the predictive scheme maintains lower interactivity delays than the simple scheme at the expense of an increase in admission delay for moderate loads. At very high loads both admission and interactivity delays of the predictive scheme are below those of the simple scheme. Note, once again, that the sudden increase in the admission delay of the predictive scheme at 70% load is due to the threshold being set to 70% which results in the sudden rise as requests begin to be delayed if the load balance is poor. As load continues to increase, this delay levels out as the algorithm

maintains a good load balance, before continuing to rise as load approaches 100%.

All of the results to date have assumed an array of 100 disks with each disk serving 10 streams. In order to complete the case studies presented here, the sensitivity of the results to each of these parameters will now be discussed. For large interactive video servers, disk arrays consisting of 100 disks with each disk serving 10 real-time streams seem reasonable within the near future. It is clear however, that such assumptions will not always hold, dependent on a range of other factors. The results shown in the following graphs vary the number of disks in the array and the number of streams being served by each disk.

6.5.3 Effect of Streams per Disk

This section considers a fixed array size of 50 disks and varies the number of streams that a single disk can service. Such a variation could be due to a different coding rate (audio files, for example will have a lower bit rate than video), or differences in the characteristics of the disk drives being used. In the cases studied here the number of streams served per device is varied from 2 to 50 streams. Interactivity rate is again assumed to be 25% and results for mean and 95th percentiles of admission and interactivity delays are shown for a utilisation level of 90% (Figure 6.15). Results for other utilisations are shown in Appendix B and are similar to those shown here.

From the admission delay graphs of Figure 6.15 it is observed that at low values of δ_1, smaller delays are possible as the number of streams per disk increases. This is also true for interactivity delays[4]. This result is expected, since a multiplexing advantage is gained as array capacity increases. Notice also that the effect of δ_1 is similar in each case although admission delay increases more rapidly with δ_1 as the number of streams per disk increases. This is due to the differencing nature of the *benefit* calculation in the predictive CAC

4. Note that the vertical scale on the interactivity delay graphs differs from that on the call admission delay graphs.

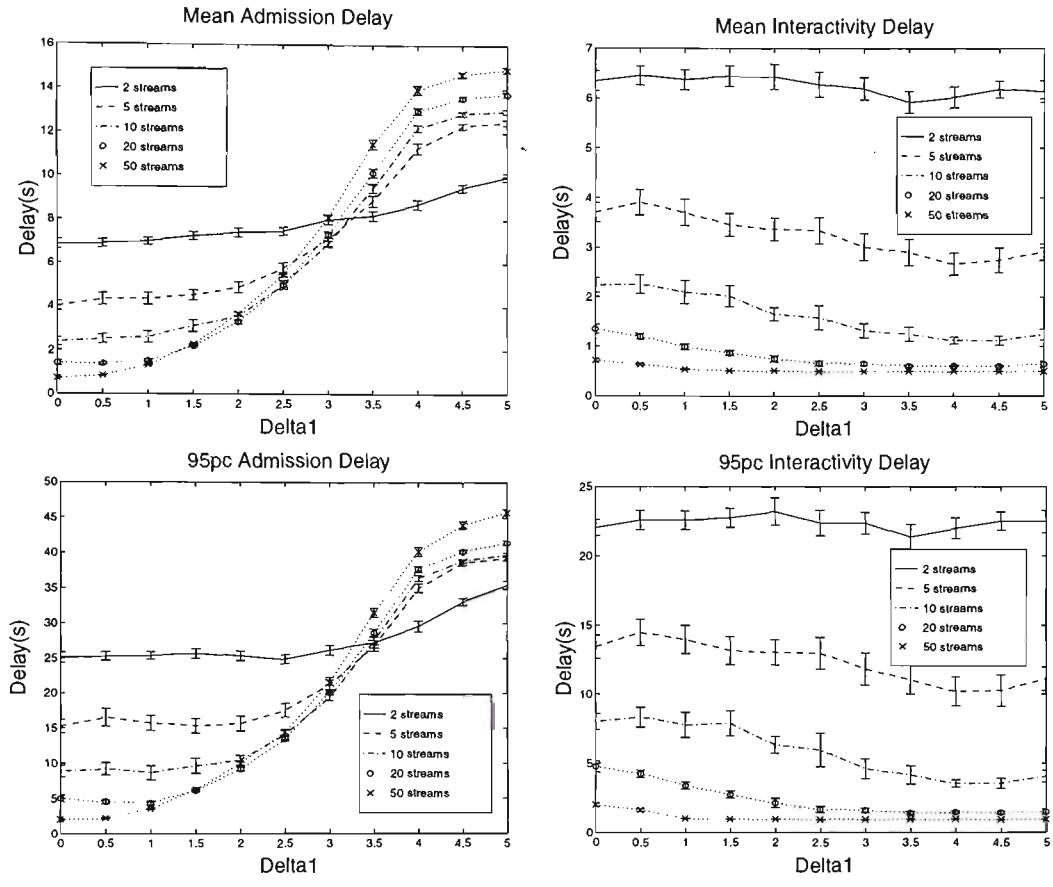


Figure 6.15 Admission and interactivity delays for a variety of streams served per disk

algorithm; and as such δ_1 must be selected based on the number of streams served by each disk. As δ_1 increases, call admission delay increases, while interactivity delay decreases. In this case the decrease in interactivity delay is modest, but as will be shown later, this is improved in situations with more disks in the array and lower rates of interactivity.

6.5.4 Effect of Disks per Array

The number of disks per array will depend on availability requirements, throughput requirements and system architecture. As has already been shown, large arrays are less reliable but have a considerable multiplexing advantage over smaller arrays. In this section the effect of array size on the CAC scheme is considered. Mean admission and interactivity delays as well as the 95th percentiles of these delays are shown in Figure 6.16.

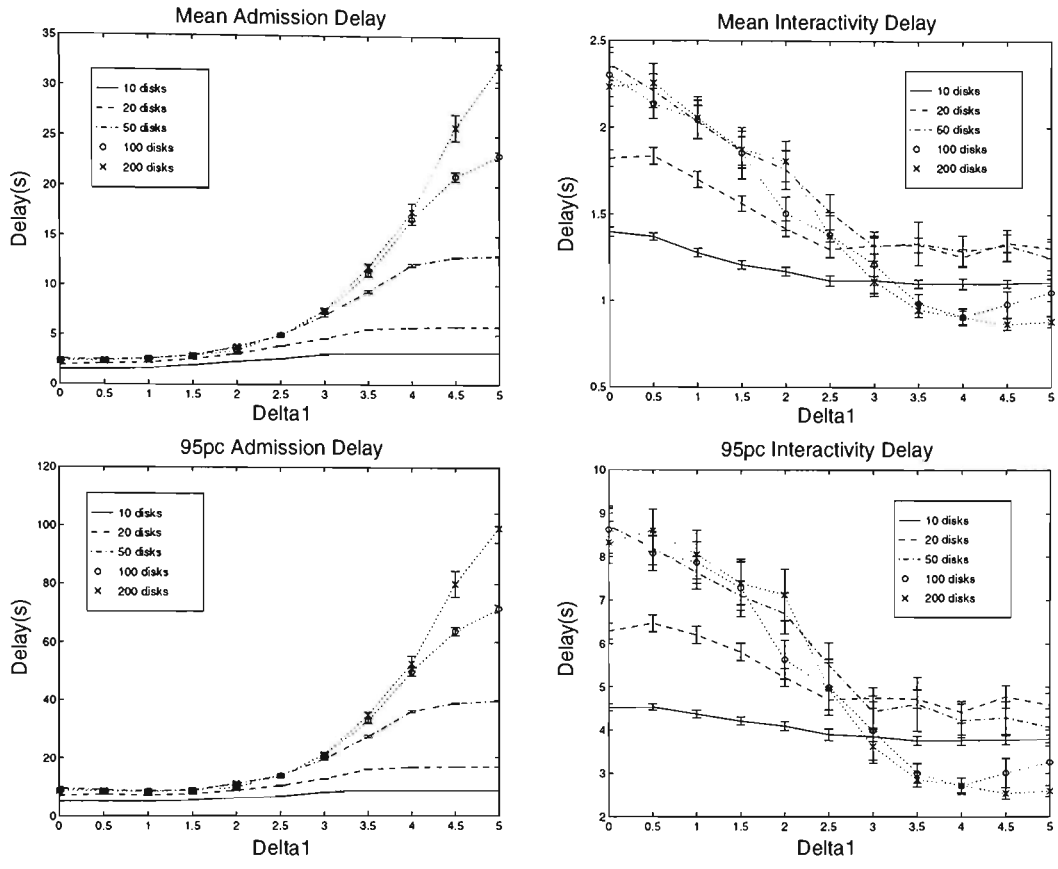


Figure 6.16 Admission and interactivity delays for a variety of disks per array

The initial observation is that call admission delay increases as array size increases. This is counter-intuitive to the idea that large arrays improve the statistical multiplexing of calls and as such can give a lower delay for the same utilisation. In fact, it is the blocking policy employed by the server that leads to this result. As shown in Figure 6.10 blocking probability of a disk array based server is accurately modelled by the Erlang-B formula. This model relies on the customers tolerating delays up to one full service cycle without being blocked (or reneging). As such the assumed delay tolerance is directly proportional to the number of disks in the array. In arrays with fewer disks, this assumed tolerance is correspondingly less and so blocking probability is increased. This increased blocking probability is what actually leads to the lower admission delays seen for smaller arrays in the figure. It should be noted that the delay tolerance of an actual user will, of course, not change depending on the number of disks in the array. For a given array size however, the assumption that one full cycle of delay will be tolerated is reasonable

in the absence of evidence to the contrary. This assumption has the further advantage of allowing the use of the Erlang-B formula to accurately model blocking.

Considering the delays versus δ_1, it is clear that in all cases, by increasing δ_1, the interactivity delay (both mean and percentiles) can be decreased at the cost of an increasing admission delay. Interactivity delay is also seen to increase as the array size increases, although this is likely to also be due to the higher level of blocking seen by the smaller disk arrays.

In Figure 6.17 a case is considered where no blocking is permitted. In this case each request is simply held until it can be served. The trend of delay versus array size is now reversed from that shown in Figure 6.16, as would be expected.

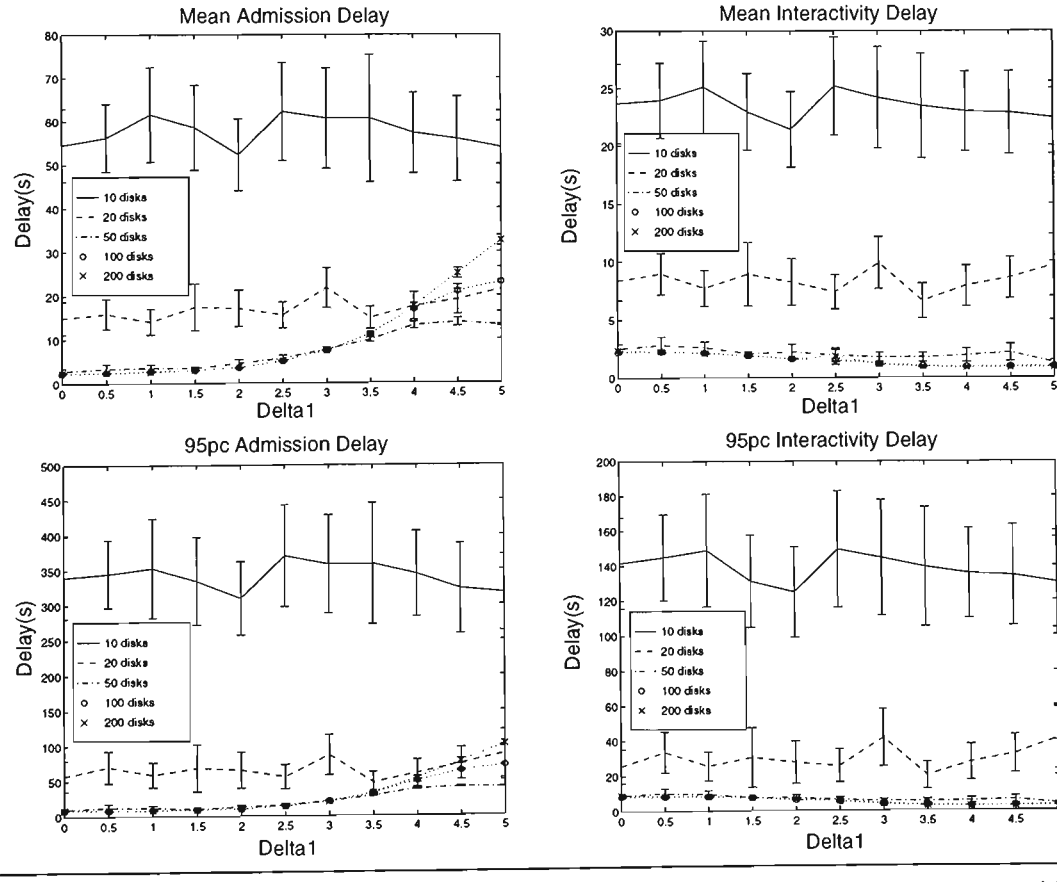


Figure 6.17 Admission and interactivity delays for a variety of disks per array with no blocking in server

The results of Figure 6.17 confirm the intuitive observation that delay is greater in smaller systems, for a given utilisation. At very

high utilisation in small systems, the queuing delay for admitting a new request becomes very large. This queueing also leads to a delay difference between admission and interactivity delays even for the simple CAC scheme (δ_1=0). Since interactivity requests are treated with higher priority than admission requests, all the interactivity requests will be served to disks where possible before admission requests are served. When there are no further interactivity requests pending for a given disk, any admission requests requiring that disk will be admitted to fill any available space. In the larger systems considered thus far, the amount of queueing of requests has been small and so for the simple CAC scheme the delay for interactivity and admission has been identical.

It should further be noted that for the small systems in Figure 6.17 that the large amount of queuing occurring leads to a reduction in the benefit of the predictive CAC scheme. In other words the value of δ_1 has very little effect on either admission or interactivity delays in these cases. Since the array is commonly fully loaded, and interaction requests are always served as soon as possible, the benefit of maintaining a balanced load is negligible. As the number of disks increases, however, the effect of queuing is reduced and the influence of δ_1 is restored.

6.5.5 Effect of Level of Interactivity

All the results to date have assumed an interactivity rate of 25%. Recalling that each interaction results in two requests to the server (one to commence and one to conclude interaction) this implies that 1/3 of requests reaching the video server are either for commencement or conclusion of interactive actions[5]. Although it is difficult to ascertain the accuracy of this assumption, it is clear that it will vary dependent on the specific application. As such it is important to consider the effect that interactivity rates have on the effectiveness of the schemes proposed here.

5. $$\frac{\text{Interactivity Rate}}{\text{Interactivity Rate + Admission Rate}} = \frac{0.25 \times 2}{0.25 \times 2 + 1} = \frac{1}{3}$$

Figure 6.18 shows the admission and interactivity delays versus δ_1 for a range of interactivities. Note that interactivity rates greater than 100% imply that each user interacts several times during a movie.

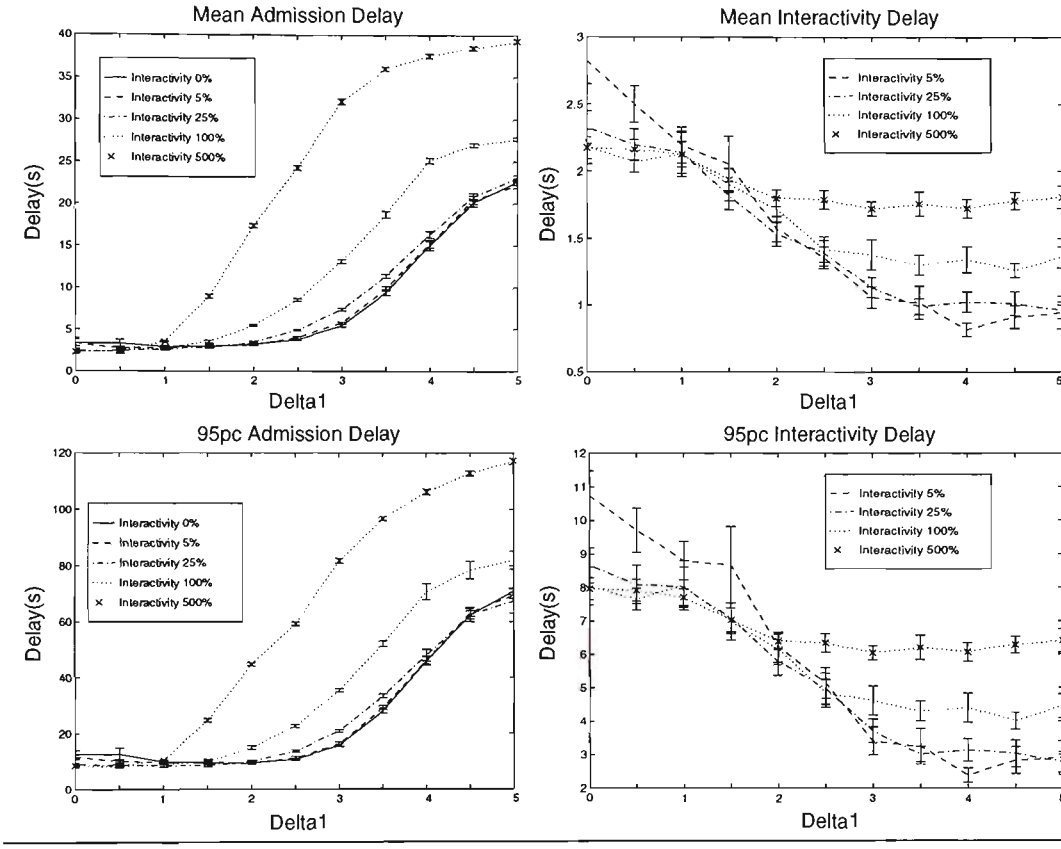


Figure 6.18 Admission and interactivity delays versus δ_1 for various levels of interactivity.

For the graphs shown, the system utilisation is 90% although the results are representative of those obtained for other utilisations. From the figure, several observations can be made. First, the call-admission delay generally increases with δ_1 as the CAC procedure attempts to improve the system load-balance. The exception to this is for an interactivity rate of 0, when the minimum call admission delay (in terms of mean and 95th percentile) actually occurs for a δ_1 value of about 1.5. This result corresponds with that obtained in Table 6.1. As interactivity rate increases, however, the call admission delay increases with δ_1. For very high rates of the interactivity the increase in call-admission delay is very severe. This is easily explained when it is considered that for an interactivity rate of

500%, 10 interactivity requests are being received for every one admission request (since interactivity requires messages for both commencement and completion). As such, the predictive CAC scheme incurs very long delays while attempting to improve the load balance of the system; an effort which is severely hindered by the large number of interactivity requests.

The graphs of interactivity delay reveal that as interactivity rate increases, the benefits obtained from the predictive CAC scheme decrease. The decrease in interactivity delay is greatest for the case with the lowest rate of interactivity (ie. the dashed line, where interactivity is just 5%). When interactivity increases to a rate of 500%, the improvement gained by the predictive CAC scheme is marginal especially considering the required increase in call-admission delay to obtain this benefit.

It is clear that the predictive CAC scheme gives most significant advantages in systems which support low-levels of interactivity. Entertainment video-on-demand systems would generally fit into this category, while educational systems would not. Depending upon the required system delay characteristics, however, it would be possible to modify the predictive CAC scheme to provide a satisfactory trade-off between admission and interactivity delay for a given application. The comparison presented here considers the simplest case, where interactivity requests must always be admitted with the highest-priority. It is likely that depending upon the type of interaction required, some requests (eg. pause/resume) may tolerate a longer delay than others (eg. FF/REW). Such a multiple priority scheme could be easily implemented merely by assigning a suitable value of δ to each request depending upon its priority. Highest priority requests would receive a $\delta_1=0$, while less time-critical requests would receive increasing values of δ_1. This extension to the predictive CAC scheme is not considered further in this thesis.

6.6 Conclusion

This chapter has introduced a novel call admission policy specifically for use in disk array based video servers. Using the semi-deterministic nature of coarse-grained disk arrays, it is possible to predict the future load on a given disk in an array. A new call request can then be delayed if it is deemed that there is sufficient benefit (in terms of improving load balance) to do so. It has been shown that such a scheme results in a reduced mean and upper percentiles of admission delay for non-interactive systems.

When interactivity is permitted, the predictions made earlier regarding future load will be affected. It has been shown that for reasonable levels of interaction the predictive scheme still performs well, and provides an efficient mechanism for differentiating between admission and interactivity requests and treating them appropriately. By variation of a single parameter (δ) it is possible to trade admission delay against interactivity delay depending upon user requirements.

One important assumption that requires further consideration is that of frequency and nature of interactivity. It is currently uncertain exactly how viewers will interact with video objects and how frequently this interaction will take place. The results presented here assume "movie" style video objects and a corresponding low interactivity rate. It is clear that other applications (eg. educational, home-shopping) can expect higher demands for interactivity, and that this increase will have a detrimental effect on the performance of the predictive CAC scheme.

Throughout this chapter a number of aspects areas have been identified as requiring further study. Specifically:

- Rigorous (analytic) methods for selecting δ_1, δ_2 and the activation threshold for the predictive CAC scheme, given particular delay constraints.
- Detailed study of the predictive CAC scheme under different interactivity implementations.

- Determining lower bounds on the optimal performance of any CAC scheme.

The scheme presented here is, however, unique in that it provides a simple way of improving load balance in a disk array. This improvement has been shown to lead to reduced admission and interactivity delays, particularly at high loads. This scheme has the significant advantage that no additional server resources are required. Other attempts at solving a similar problem have required additional buffering which would incur considerable cost [Vin94b].

7. Case Study: Interactive Video Network Design

It's not enough to be busy. The question is: What are we busy about?

- Henry David Thoreau

7.1 Introduction

This chapter utilises the results from the earlier chapters to provide an example design for a realistic interactive video network scenario. In the literature to date, the author has not seen a complete interactive video network design study. Previous work has dealt with a subset of the overall problem, but rarely with reference to other aspects, as discussed in Chapter 2. Although little new material is presented in this chapter the overall design methodology is a significant contribution in itself. A detailed case study is used to illustrate the design methodology in detail.

The design methodology presented here is only one of a number of possible approaches. The method used here is, however, a logical one based on the likely set of parameters that a designer will have to deal with. It is common for an engineering design process to be iterative, with the results of a first pass being fed back in to the process to provide further refinements [Cros94]. Our method is no exception to this rule and as always, human experience and skills will undoubtedly prove invaluable in the design of such systems. The tools presented in earlier chapters and utilised here, however, pro-

vide the system designer with a powerful starting point for such design undertakings.

7.2 Design Methodology

As already mentioned most design procedures are iterative. That is, an initial design will be completed based on a set of assumptions, and the results of this will feed back into the design process resulting in some changes to the assumptions and in turn an improved design. Although such iteration is necessary, its use is minimised by applying a logical design procedure throughout. In this section we present a flowchart for design of interactive video systems that utilises much of the work presented in this thesis in creating a logical and ordered design procedure.

The flow chart of the design process proposed here is shown in Figure 7.1. Note that this flowchart follows the same top-down approach to the problem that has provided the structure for this dissertation. The problem is initially considered at the network level, before considering individual servers, disk arrays and finally single video objects. This top-down approach is a standard engineering technique which can be applied to all manner of design problems.

The inputs to each stage of the process are shown on the left of the figure while outputs from each stage are shown on the right. Although not shown explicitly a large number of outputs flow from one stage to the next to be utilised in more detailed aspects of the design. It is only the final outputs that are shown on the right hand side. As with many design procedures it is possible that in some cases the inputs shown here would actually be the desired outputs of the design process or vice versa. This fact is easily incorporated into the design procedure shown.

Rather than discussing each of the blocks of Figure 7.1 in an abstract sense the remainder of this chapter provides more detail by

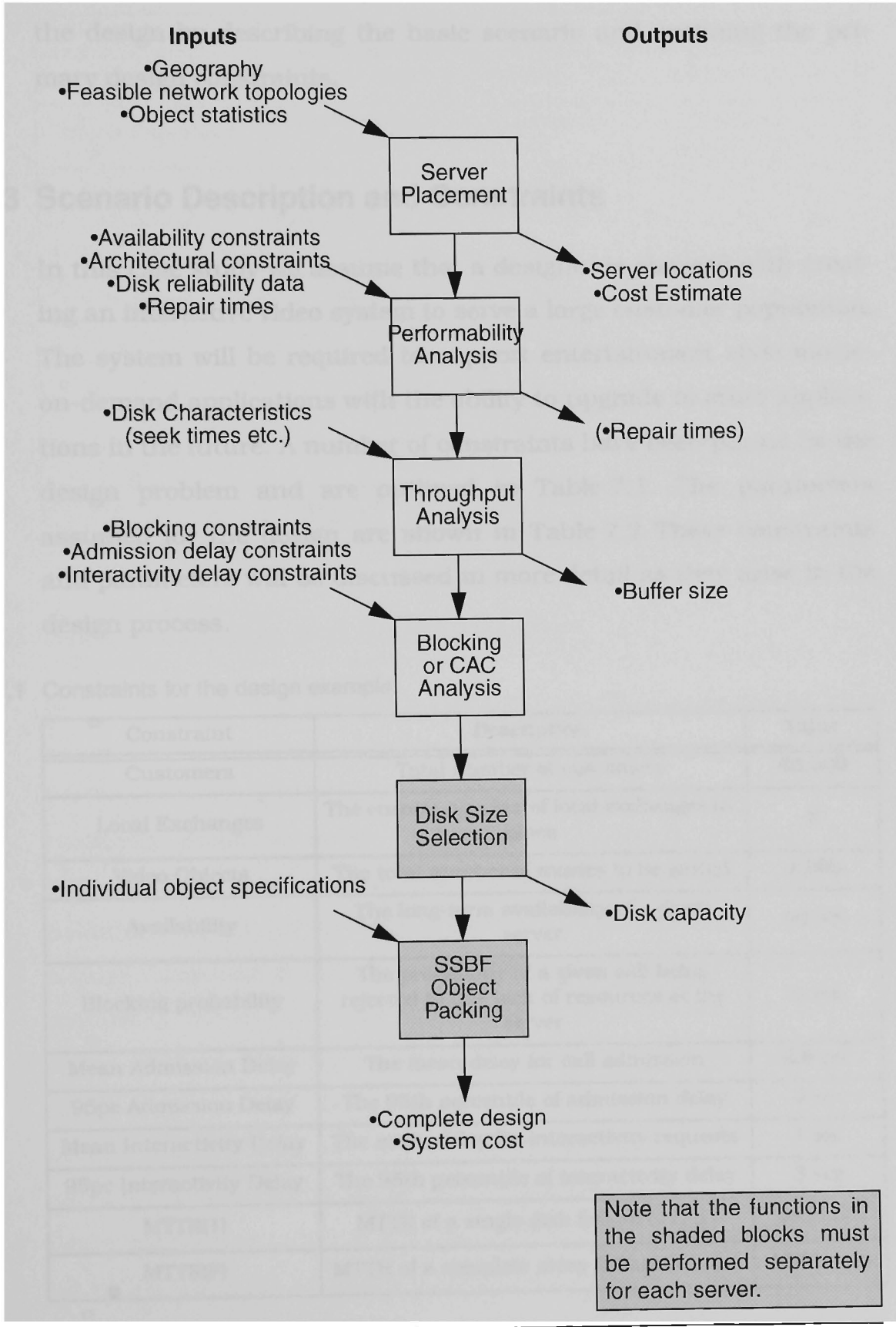


Figure 7.1 Top-down design procedure for interactive video networks

way of a fully worked design example. The next section commences the design by describing the basic scenario and outlining the primary design constraints.

7.3 Scenario Description and Constraints

In this case study we assume that a designer is charged with creating an interactive video system to serve a large customer population. The system will be required to support entertainment style movie-on-demand applications with the ability to upgrade to other applications in the future. A number of constraints have been placed on the design problem and are outlined in Table 7.1. The parameters assumed for the design are shown in Table 7.2 These constraints and parameters will be discussed in more detail as they arise in the design process.

Table 7.1 Constraints for the design example.

Constraint	Description	Value
Customers	Total number of customers	60,000
Local Exchanges	The current number of local exchanges in place	6
Video Objects	The total number of movies to be stored	1,000
Availability	The long-term availability of a given server	99.5%
Blocking probability	The probability of a given call being rejected to due lack of resources at the server	0.1%
Mean Admission Delay	The mean delay for call admission	2.5 sec
95pc Admission Delay	The 95th percentile of admission delay	5 sec
Mean Interactivity Delay	The mean delay for interactivity requests	1 sec
95pc Interactivity Delay	The 95th percentile of interactivity delay	3 sec
MTTR(1)	MTTR of a single disk failure ($=1/\mu$)	48 hours
MTTR(F)	MTTR of a complete array failure ($=1/\mu'$)	168 hours

Table 7.2 Parameters used for the design example.

Parameter	Description	Value
MTTF	MTTF of a single disk drive ($= 1/\lambda_s$)	200,000 hours
Object Popularity	The distribution of requests to individual movie titles	Empirical (Equation 3.8)
Disk Cost	Model relating disk cost to capacity	$P = K_2C + K_1$ $P = 0.275C + 188$ (Equation 3.5)
C_T	Capacity of a disk track	51,000 bytes
t_1	See Equation 4.2	0.0152 seconds
t_2	See Equation 4.2	0.0167 seconds
K_B	Cost of buffering	$50 / MB
R_1	Stream rate	375,000 bytes/sec
p	Proportion of reward earned by a RAID 5 in a partially failed state	0.765 (from Figure 4.7)

7.4 Network Design and Cost Estimate

In this example it is assumed that the total customer population is connected to the core network via six local exchanges in the existing POTS network - 10,000 connections per exchange. It clearly makes economic sense to utilise the physical locations of these local exchanges as front-end servers for the interactive video network. Assuming a peak activity rate of 40% (see Figure 4.7) this equates to a busy hour load of 4,000 streams per FES. Now, given the object popularity model developed in Chapter 3, it is known that a knee exists at about 60 movies which will account for approximately 85% of all requests, and that caching this level of requests minimises overall system costs (see Chapter 3). This implies that a FES will serve 3,400 streams (peak) by storing just 60 objects. The total overflow traffic (those requests not able to be served from the cache) from all FES's will thus be about 3,600 streams during busy hour. It is reasonable to expect that these streams could be adequately served by a single video server located in the core network storing all 1,000 objects.

Note that the above network level analysis is deliberately approximate. It is intended to give an overall picture of the network design based on a small amount of input data. The details of the design are refined during the next stages and the results of this section can be iteratively altered as required. From this basic network design, however, it is possible to determine a cost estimate for the system based on the methods presented in Chapter 3. We reiterate that this cost estimate is for storage only and does not include bandwidth or maintenance costs. The results of this cost estimate are shown in Table 7.3.

7.5 Performability Analysis

Given a high-level view of server placement and dimensioning it is now possible to design the storage subsystem of each of the individual servers. Each server will consist of several disk arrays with each array made up of a number of disk drives. In this section it is assumed that a certain minimum system availability will be specified, and this will be used to constrain the maximum number of disks in the array. It should be further noted that architectural considerations dependent on current disk array and interconnection technologies may place a tighter constraint on array size than that determined by the availability requirement.

Availability is defined here as the percentage of time during which the server is able to serve a full complement of requests. This can be directly equated to the performability measure of reward earned as a percentage of available reward over a given mission time. The assumption of an availability requirement of 99.5% implies that over a long time period, the server should be "up" for a proportion of time that is sufficient to enable it to serve that percentage of the requests. Of course, as seen in chapter 4, a RAID 5 based server actually operates in one of 3 states, meaning it cannot be considered as merely "up" or "down" at any time. The performability model developed in

Chapter 4, however, allows us to account for this in the availability analysis. Appendix C derives Equation 7.1 as an upper limit for the number of disks per array.

$$D \le \left\lfloor \frac{-b + \sqrt{b^2 - 4ac}}{2a} \right\rfloor \quad \text{where} \quad \begin{aligned} a &= A\lambda_s^2 \\ b &= 2A\lambda_s\mu' - A\lambda_s^2 - \lambda_s\mu' - p\lambda_s\mu' \\ c &= \lambda_s\mu' + A\mu\mu' - \mu\mu' - A\lambda_s\mu' \end{aligned} \qquad \text{(Eqn 7.1)}$$

For the values assumed here, this equation results in an upper limit of 73 disks for each array.

7.6 Throughput Analysis

This phase of the design process determines the throughput that a disk array of the size already determined can maintain. The inputs to this phase include the detailed disk parameters (seek time, rotational speed, capacity of each track etc.), the disk cost model and the stream rate of the video objects stored (see Table 7.2). Buffer size per stream can be an input or can be calculated so as to minimise total system cost by using Equation 4.20 (reproduced here).

$$B_5 = \sqrt{\frac{K_1 R_1 t_2}{K_B}} \qquad \text{(Eqn 7.2)}$$

The corresponding throughput obtained from a RAID 5 disk array is obtained from (Equation 4.6):

$$R_5 = \frac{B_5 D}{(B_5/C_T)t_1 + t_2} \qquad \text{(Eqn 7.3)}$$

which results in a sustainable throughput of 512 streams for each 73 disk array, and a buffer size of 204 kbytes per stream (rounded to the nearest whole disk track).

7.7 Blocking and CAC Analysis

Given the "raw" throughput that can be sustained by an array, this phase of the design procedure sets a limit on the number of streams to be assigned to the array such that a given blocking probability or admission or interactivity delay constraint can be ensured. The limit placed on the number of streams to be served by the array as a result of these constraints is termed the "effective bandwidth" of the array. The effective bandwidth is determined by initially setting it to be equal to the raw bandwidth and then considering each constraint in turn and successively marking down the previous value of effective bandwidth until all constraints are met. Once again an iterative process may be desirable if certain constraints are easily met while others are not.

First, consider blocking probability. Chapter 6 showed that blocking probability of a large disk array can be accurately modelled by Erlang's B formula, under the assumption that customers will be willing to wait for one full service round of the array. If customers are willing to wait longer (and the server permits this), then this forms a worst case bound on blocking probability, which is desirable from a designers point of view. Utilising the Erlang B formula (Equation 5.8) it is determined that the upper limit of utilisation for a server capable of serving 512 streams is 90% or a maximum busy-hour load of 460 streams to ensure a maximum blocking probability of 0.1%.

Determining the limits of admission and interactivity delay require more careful consideration, due to the complex nature of the relationship between these two delays and the δ values of the predictive CAC scheme. From the results of Chapter 6 we are able to define contour plots that give feasible regions of operation given particular delay constraints. Appendix C uses this method to determine that the maximum utilisation which meets the delay constraints of Table 7.1 is 88%, and that δ_1=1.8 and δ_2=0 achieves the required delays at this utilisation. As such the raw bandwidth of 512 streams

must be further marked down to an effective bandwidth of just 450 streams. This result can now be used as an input into the final stage of the design process which selects disk capacity and actually allocates objects to disk arrays.

7.8 Disk Size Selection and Object Packing

All of the previous results apply to both the FES and VS design. In this section it is necessary to consider the disk size selection and object packings separately for the FES and VS.

7.8.1 Front-End Server

Given that each FES must cater to a peak load of 3,400 streams and a single array can support a load of 450 streams, it is clear that:

$$\left\lceil \frac{3400}{450} \right\rceil = 8 \qquad \text{(Eqn 7.4)}$$

disk arrays will be required. Storage required for 60 movies (at 100 minutes each, including trailers etc.) will be:

$$60 \text{ movies} \times 375,000 \text{ bytes/sec} \times 100 \text{ min} \times 60 \text{ secs/min} = 135 \text{ GB} \qquad \text{(Eqn 7.5)}$$

and since this storage will be provided by a total of 584 disks (8 arrays of 73 disks each), the required storage per disk is given by:

$$\frac{135 \text{ GB}}{584 \text{ disks}} = 231 \text{ MB/disk} \qquad \text{(Eqn 7.6)}$$

Although by modern standards such a disk capacity requirement is small, such drives are still available and can be shown to fit the cost model presented in Chapter 3. Indeed the Maxtor 7273A is a 270MB drive with almost identical performance characteristics to those assumed for this study[1]. If this drive is selected it will actually provide slightly more capacity than the 231MB required which will (ideally) allow the FES to store several additional movies over the 60 that

1. It is important to ensure that the selected drive does match the assumed performance characteristics, if not the appropriate steps of the design procedure should be repeated with the appropriate values for the disk drive selected.

were initially specified. The extra "slots" will ensure that the caching algorithms are efficient enough to ensure that the FES does serve 85% of requests as was originally assumed. The results of the object packing are shown in Appendix C, where it is demonstrated that SSBF consistently meets the lower bound of 8 arrays while other heuristics require 10 or more arrays.

7.8.2 Core Video Server

Given that the core video server will be required to serve 3,600 streams and store 1,000 objects the disk requirement and packing problem will be considerably different to that of the FES. Using a similar method to that in Section 7.8.1 the minimum number of arrays required can be determined to be 8 and the required disk capacity is determined to be 3.85GB. This drive capacity is clearly much larger than that required in the FES. This is due to the much smaller bandwidth to space ratio required in the core video server. A much larger number of objects is now being stored, while not serving a significantly greater number of streams. Once again, however, the required disk capacity is well within the range of available devices and a Seagate 15150W would be suitable choice with a capacity of 4.1GB and similar performance characteristics to those assumed above. The results of the object packing are shown in Appendix C (Section C.4.2) where the minimum number of bins required is shown to be 9, once again obtained by the SSBF heuristic.

Following the packing of the FES and VS with video objects the system design is complete and the total storage cost can now be accurately determined. Assuming that each FES has the same design the cost of each one can be determined from:

$$\begin{aligned} \text{FES Cost} &= 8 \text{ arrays} \times 73 \text{ disks/array} \times (200 + 0.273 \times 280) \\ &= \$160,950.40 \end{aligned} \qquad \text{(Eqn 7.7)}$$

Similarly, the core VS storage cost is easily determined from:

$$\begin{aligned} \text{VS Cost} &= 9 \text{ arrays} \times 73 \text{ disks/array} \times (200 + 4.1 \times 280) \\ &= \$885,636 \end{aligned} \quad \text{(Eqn 7.8)}$$

and the total storage cost of the entire system is obtained by adding the costs of 6 FES's and a single VS:

$$\begin{aligned} \text{Total Cost} &= 885,636 + (6 \times 160,950.40) \\ &= \$1,851,338.40 \end{aligned} \quad \text{(Eqn 7.9)}$$

This total system cost is seen to be about 10% more expensive than that obtained by the cost estimate in Section 7.4. This increase can be primarily attributed to the requirement for 9 arrays for the VS rather than the 8 originally indicated by the lower bound. Despite this aberration, the two costs are in generally good agreement, as are the cost estimates for the FES and VS components individually.

Table 7.3 Primary results of the design example.

Result	Value
Maximum Array Size	73 disks
Required Buffer Size (per stream)	204 kbytes
Raw Array Bandwidth	512 streams
Effective Array Bandwidth	450 streams
Predictive CAC δ_1	1.8
Predictive CAC δ_2	0
FES Disk Capacity	230 MB
Suitable FES Disk Model	Maxtor 7273A
FES Cost Estimate	$159,830
Actual FES Cost	$160,950
VS Disk Capacity	3.85 GB
Suitable VS Disk Model	Seagate 15150W
VS Cost Estimate	$718,610
Actual VS Cost	$885,636
System Cost Estimate	$1,677,590
Actual System Cost	$1,851,338
Discrepancy between Cost Estimate and Actual System Cost	10.3%

This completes the design process. Table 7.3 shows a summary of the results obtained. A system designer is, of course, free to examine the effect of various constraints and loosen or tighten them to determine the sensitivity of the system design. The systematic method outlined here is particularly amenable to such iteration and the design presented here could probably be further optimised by relaxation of just a few of the constraints listed in Table 7.1

7.9 Conclusion

Although not particularly exhaustive, this case study has completed an entire system design using the tools developed in this thesis. Importantly, it has been demonstrated that the cost function developed in Chapter 3 provides reasonably accurate cost estimates without the need for a detailed design. Provided that this cost estimate is acceptable, the detailed design can proceed in a logical and systematic fashion to determine an overall system specification. By following this methodology, a system designer can be confident that the resulting design will satisfy a given set of quality-of-service constraints and will operate efficiently and at minimal cost.

The example presented here has been intentionally simplified in a number of ways. The aim has not been to account for every factor that may influence a system implementation. Instead the goal has been to demonstrate the application of tools developed throughout this dissertation. The result of this demonstration has been a top-down design methodology that utilises the work of the previous chapters in a logical and modular fashion. Each stage of the process produces outputs that either form inputs to the next stage or define part of the final system design.

The methodology presented here is the only attempt to present a unified design approach to interactive video systems that this author has encountered. Previous work has solved parts of the problem or

taken a high-level view to develop cost estimates but without resolving sufficient detail to be classified as a complete system design [Doga95] [Tetz94]. The approach presented here (and summarised in Figure 7.1) makes a significant contribution by providing designers with a powerful system from which to base any large-scale design.

8. Conclusion

This morning I took out a comma and this afternoon I put it in again.

- Oscar Wilde

8.1 Overview

Interactive video services are likely to form the basis for a range of exciting new telecommunications applications. For this reason, recent years have seen a continuing increase in research efforts dedicated to the provision of these services in an efficient manner. While some of the many problems now have good solutions, several are still poorly defined or inadequately dealt with by existing methods. This dissertation has identified several key areas of interest and provided analysis and design methods suitable for solving some of the problems. Specifically, the following areas have been examined in detail:

- Network design and storage placement.
- Performance and reliability of disk array storage subsystems.
- The allocation of objects to individual disk arrays.
- Call admission control schemes to minimise load imbalance in the disk array.
- Design methods for large scale interactive video systems.

Throughout the dissertation, video-on-demand (VOD) has been used as a representative application of interactive video services. Where detailed input parameters have been required, they have been taken from the VOD application wherever possible. Recent market research indicates that VOD will at least initially be the dominant application using interactive video services. This fact combined with the availability of useful data from video rental stores and the movie industry, makes VOD the most suitable candidate for the case studies presented here.

The following sections highlight the major results obtained in each part of the thesis.

8.2 Network Design

Previous cost analyses of interactive video networks have made simplifying assumptions with little justification with regards to the nature of storage and network topologies. The analysis presented in Chapter 3, however, derives a cost model based closely on a realisable video server architecture. The assumption that storage costs are dominant in servers allows the cost model to be based purely on storage costs. The cost model derived is applied to distributed and centralised storage systems using a VOD-type workload and it is revealed that a distributed system (with storage located close to user populations) results in reduced overall system costs. Importantly, this result comes about without accounting for bandwidth savings arising from a distributed approach. Previous work has shown that such savings are also significant, resulting in further reduced operating costs when storage is distributed to Front-End Servers. It should be noted that although the methodology used here is unique, the results obtained are in good agreement with existing studies.

The benefit of distributed storage is reliant upon the FES's storing only the most popular titles. Caching algorithms are required to

ensure that this remains true as popularities change over time. Chapter 3 develops several caching algorithms and demonstrates that even though simplistic, they are sufficient to maintain good cache currency, and ensure the cost effectiveness of the storage located at the FES.

8.3 Server Design

Much research has focused on building high-performance video servers using disk array technology. The reliability of these same servers has, however, received little attention. It is generally assumed that RAID mechanisms can be applied to these disk arrays to ensure almost fault-free operation. Chapter 4 investigates this issue in some detail and identifies the key trade-offs between the two most commonly supported levels of RAID: 3 and 5. While RAID 5 arrays are less expensive for a given throughput, they degrade significantly following a single disk failure. RAID 3 maintains the same performance following a failure, but costs significantly more initially. A performability model is employed to account for these factors and several case studies are used to demonstrate the benefit of RAID 5 over RAID 3 in read-only video server applications.

8.4 Object Allocation

The problem of placing video objects (movies) onto disk arrays within a server seems trivial. It is easy to show, however, that this problem is in fact NP-hard. Further the problem can be identified as analogous to the two-dimensional vector packing (2DVP) problem. Previous heuristics proposed for near-optimally solving this problem are derived from the bin-packing First-Fit (FF) and First-Fit Decreasing (FFD) heuristics. Unfortunately these heuristics can perform poorly when the object dimensions are not uniformly distributed.

In the case of interactive video systems the object dimensions represent bandwidth and capacity requirements and are not uniformly distributed. The bandwidth dimension is heavily-skewed, while the capacity dimension exhibits a Gamma-like distribution. To pack such objects efficiently, a new heuristic - termed Same-Shape-Biggest-First (SSBF) - is proposed. This heuristic is applied to a number of case studies and shown to give significant improvements in terms of packing efficiency at the negligible cost of increased execution time.

8.5 Admission Control

Typical CAC schemes admit a new request provided only that it will not exceed the upper limit of the resources available at the video server. This can lead to significant load imbalance across a large coarse-grained disk array. In turn, this imbalance results in high delay variability for new requests as the system becomes heavily loaded. Chapter 6 develops a predictive CAC scheme which utilises load information from all disks in the array to determine when to admit a new request. By selectively delaying certain requests, overall delay can be reduced and delay variability reduced quite substantially. Importantly, no additional resources are required to provide this benefit.

When interactivity is permitted, the predictive scheme is further able to differentiate between admission and interaction requests in order to satisfy different delay requirements for each. For moderate levels of interactivity, the predictive scheme maintains a good load balance while also admitting interaction requests with lower delay than the admission requests. The scheme proposed in Chapter 6 does require further study with respect to different types and greater levels of interaction. The results presented are, however, very promising, considering they come at zero cost, since no additional resources are required.

8.6 Design Methodology

Designing a large-scale interactive video system is clearly a significant undertaking. Without some logical methodology, a system designer will be unlikely to produce an efficient and cost-effective design. Chapter 7 presents an appropriate methodology making specific use of the work presented in earlier chapters. While the method presented does not represent a significant departure from traditional design methods, it is the first complete design process that this author has encountered. The method is iterative and allows a designer to experiment with various options and to easily change inputs and outputs of the process to assist in ensuring that the resulting design will perform as required at minimum cost.

8.7 Further Work

The majority of the results presented in this dissertation use video-on-demand as a representative application for interactive video services. The important input parameters have been derived from limited market research data and statistics from video rental stores. It is somewhat unclear how closely the future VOD application will actually map to these statistics. As such, an important area of future work is related to characterising the workload that will be placed on interactive video services. Such work will involve market research, human factors research, trial systems and large-scale rollouts. With accurate workload models for a range of interactive video applications it will become possible to further refine the design and analysis methods presented here.

With reference to the performability analysis of Chapter 4; the construction of large disk arrays using new high-bandwidth interconnection technologies still requires further study. Several groups are investigating the use of ATM at the device level and it is this type of technology that will allow the construction of very large, easily scala-

ble, disk arrays. To date, however, only small prototype systems have been developed using this approach.

The predictive CAC scheme of Chapter 6 shows potential for providing improved delay performance of disk array based video servers. Several areas do, however, require further study. Specifically, analytical models should be developed to facilitate the selection of appropriate values of δ_1 and δ_2 for a given set of user requirements. Further, the predictive algorithm itself, may be able to be further improved and lower bounds developed to prove the quality of such an algorithm.

Most importantly, though, research is ongoing on each of the technologies that make interactive video services possible. Storage, compression and networking technologies continue to improve. The major future work is therefore related to the deployment and operation of these systems. Although there is much still to be learned, this cannot happen until a greater understanding of the systems is developed. This understanding will only come about once the systems are deployed to the public on a large-scale.

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Appendix A. Optimisation of Disk Size Allocation

This appendix discusses a simple optimisation scheme for improving the allocation of objects to disks in an heterogeneous disk array. The proposed scheme can be shown to provide a marginal improvement over the methods already discussed in Chapter 3.

Once an initial allocation of movies to disks has been performed, this is able to be optimised to some degree by combining several fractional disk usages together onto a single disk. An example of this type of optimisation is shown in Figure A.1.

The algorithm used to perform this optimisation is as follows. Let D_j represent the rank of the lowest ranked movie to be stored on disks of size G_j.

$$D_j = (\max(i) : C_i = G_j) \qquad \text{(Eqn A.1)}$$

The total disk requirement for each capacity is then determined from a simple modification to Equation 3.4:

$$d_j = \sum_{i = D_{j-1}+1}^{D_j} \left\{ \max\left(\frac{NBp_i}{L}, \frac{S_i}{C_i} \right) \right\} \qquad \text{(Eqn A.2)}$$

Once this initial requirement has been determined, the optimisation algorithm begins with the largest disk and attempts to relocate

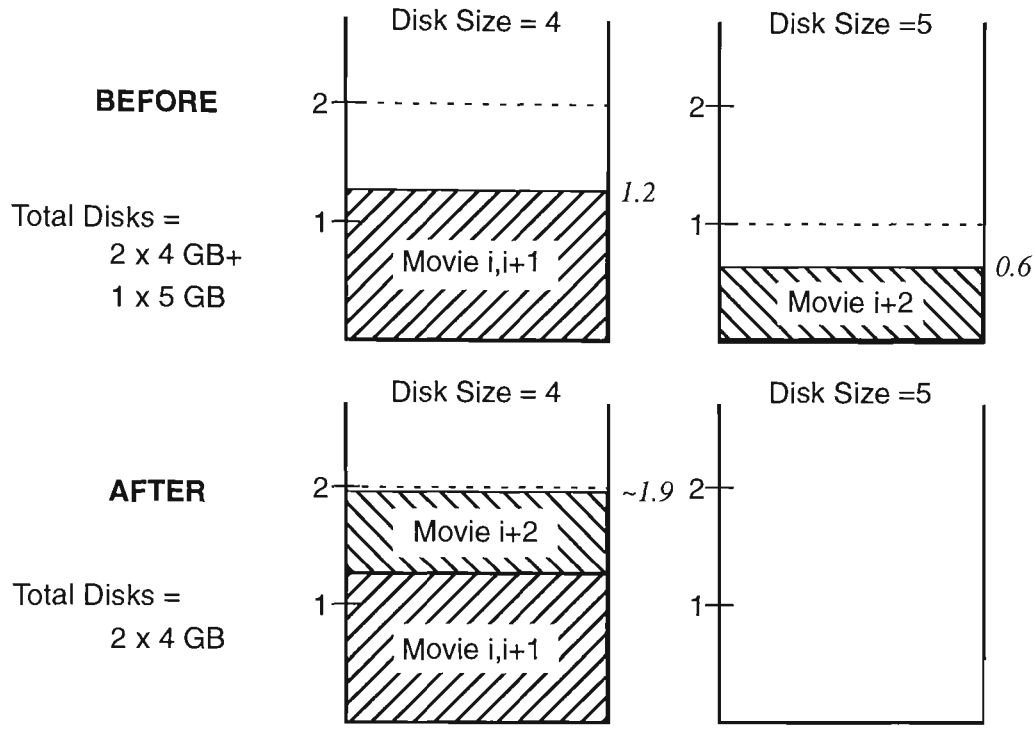

Figure A.1 Optimisation of movie allocation example

movies onto smaller disks without increasing the cost of the smaller disk. Movies are shifted from the larger disk to the next smallest disk size until no more movies can be shifted without increasing the smaller disk requirement. If a reduction in the larger disk requirement is achieved by performing these relocations then the relocations are accepted and made permanent. Alternatively, if no improvement to the larger disk count is brought about then the changes are undone and the algorithm moves to consider the next smallest disks size. The algorithm is shown in Figure A.2.

Although we don't discuss this algorithm in detail here, it is shown in [Barnett96a] to provide a slight improvement over the standard heterogeneous case. The optimality of this approach is not a focus of this thesis, instead it is a simple heuristic approach which can be used to improve any disk layout selected by the heterogeneous scheme presented in Chapter 3.

```
for i = biggest disk to smallest disk
        save initial disk state
        for j = highest ranked movie on i to lowest ranked movie on i
                d_new(i) = d(i) - disk_req(j)
                d_new(i-1) = d(i-1) - disk_req(j)
                if ((⌈d_new(i)⌉ ≤ ⌈d(i)⌉) AND (⌈d_new(i-1)⌉ ≤ ⌈d(i-1)⌉))
                OR ((⌈d_new(i)⌉ < ⌈d(i)⌉) AND (⌈d_new(i-1)⌉ ≤ ⌈d(i-1) + 1⌉)) then
                        /* beneficial to move */
                        d(i) = d_new(i)
                        d(i-1) = d_new(i-1)
                else
                        /* unable to move this movie without incurring penalty */
                        if (⌈d_new(i)⌉ ≥ ⌈d(i)⌉) then
                                /* No benefit was gained */
                                restore initial state
                        end
                        /* exit the inner loop */
                        break
                end
        end
end
```

Figure A.2 Algorithm for heterogeneous disk array movie allocation optimisation

Appendix B. Further Results for the Predictive CAC Scheme

This appendix presents more detailed results for several cases studies of the predictive CAC scheme discussed in Chapter 6. Although the 3-dimensional nature of the plots makes precise quantitative comparisons difficult, the intention here is merely to examine trends. Confidence intervals are omitted for clarity, and no discussion is presented here, since all results comply with the trends discussed in Chapter 6.

Figure B.1 shows the mean admission and interactivity delays versus the number of streams being served per disk for an array consisting of 50 disks. Figure B.2 shows the corresponding 95th percentile delay results.

The mean and 95th percentiles of delay are shown in Figure B.3 and Figure B.4 respectively, for cases where the number of disks in the array is varied, and each disk serves 10 streams.

Figure B.5 reveals the mean delay results in a system where no blocking is implemented. All requests (interactivity and admission) are queued until they can be served, hence the reversal in the trend from Figure B.3.

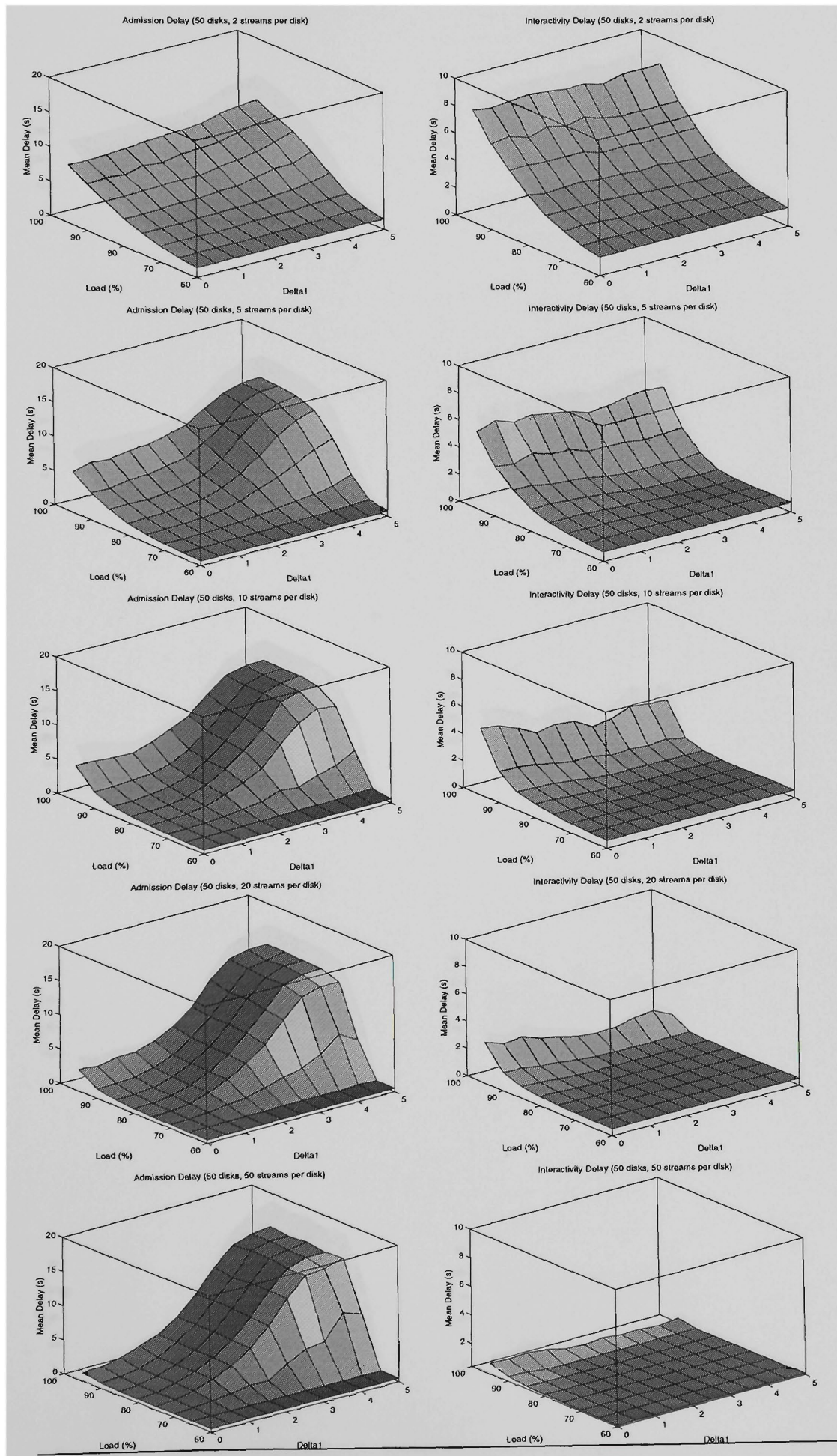

Figure B.1 Mean admission and interactivity delay vs number of streams

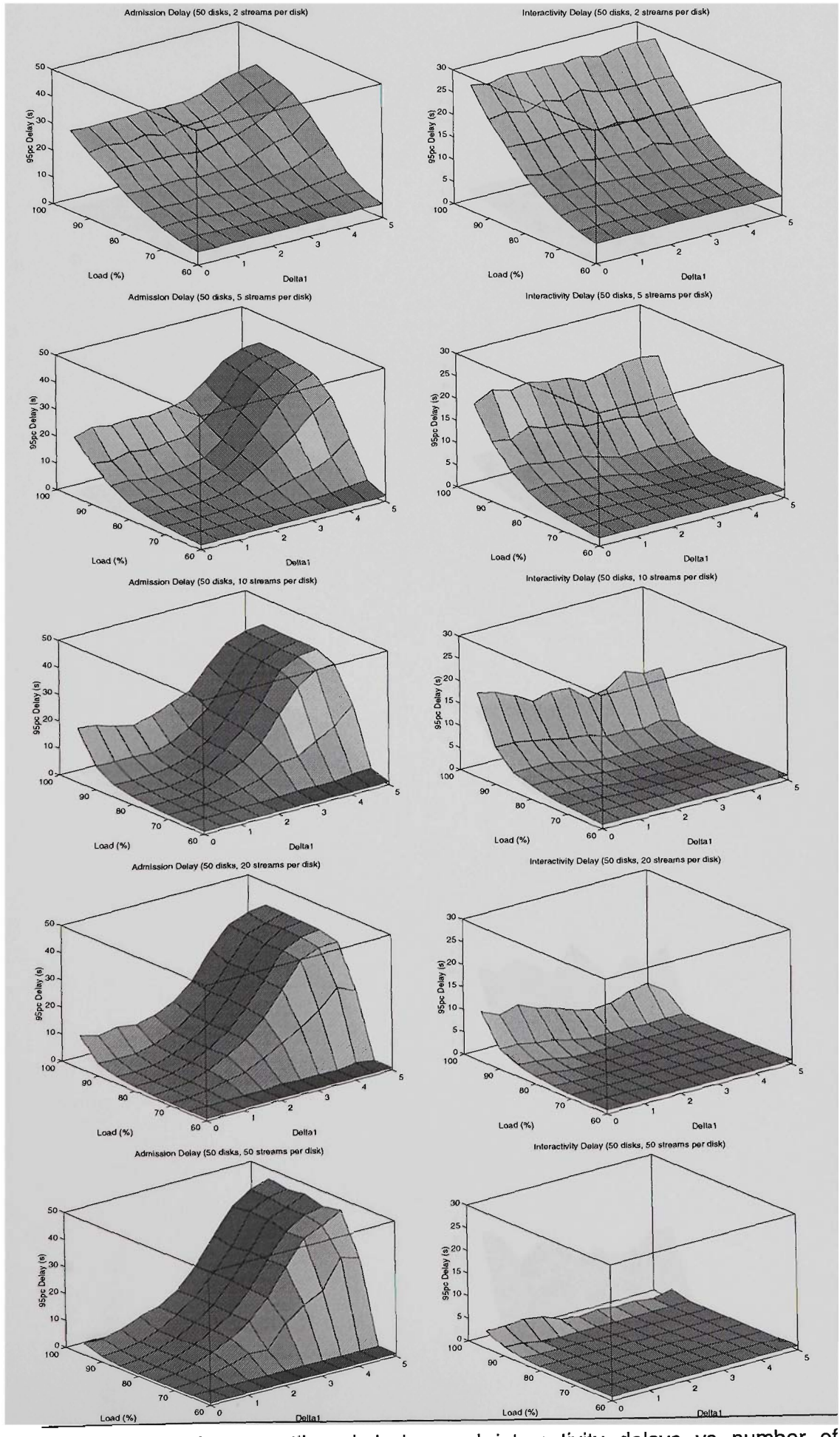

Figure B.2 95th percentile admission and interactivity delays vs number of streams

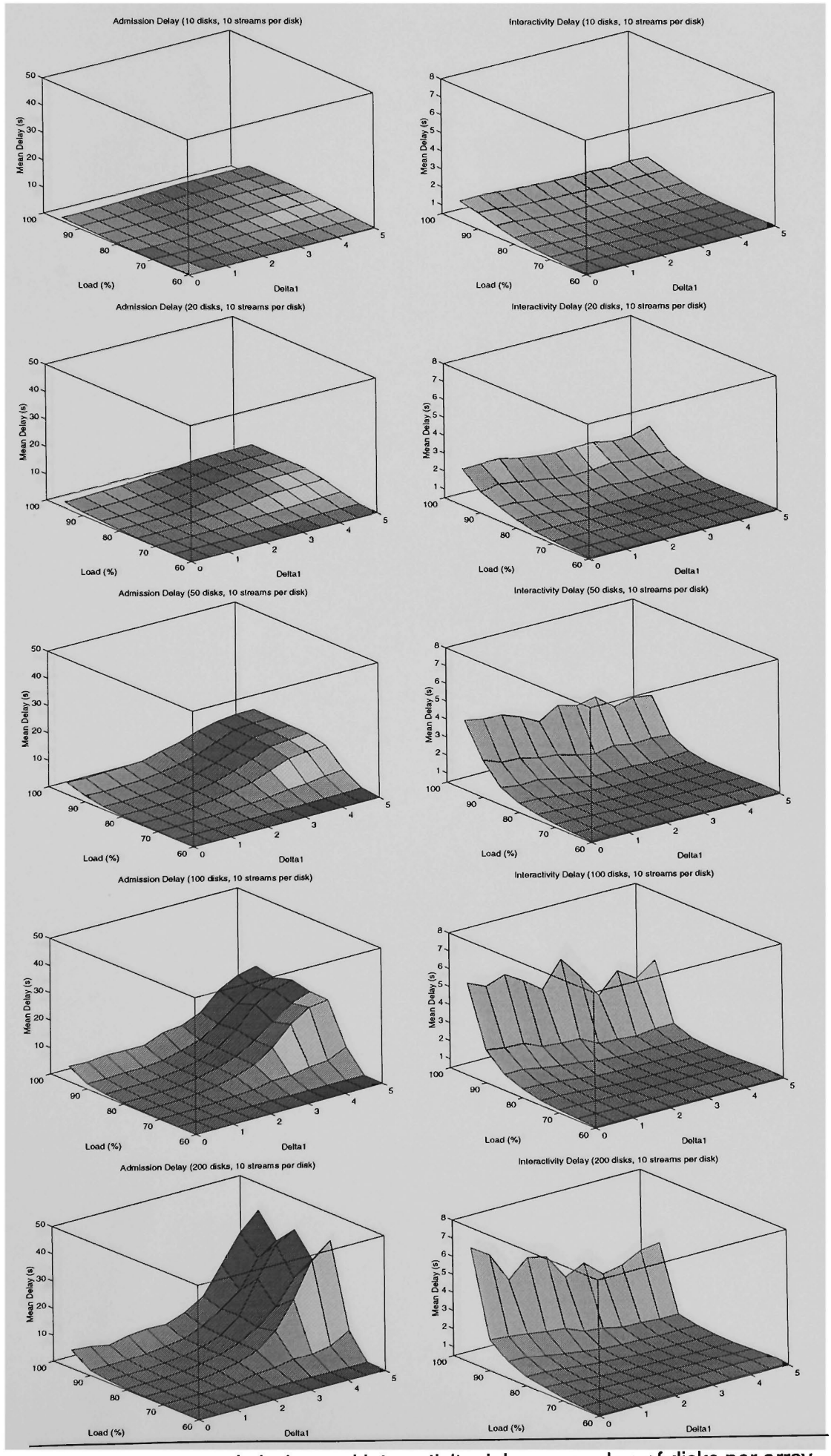

Figure B.3 Mean admission and interactivity delay vs number of disks per array

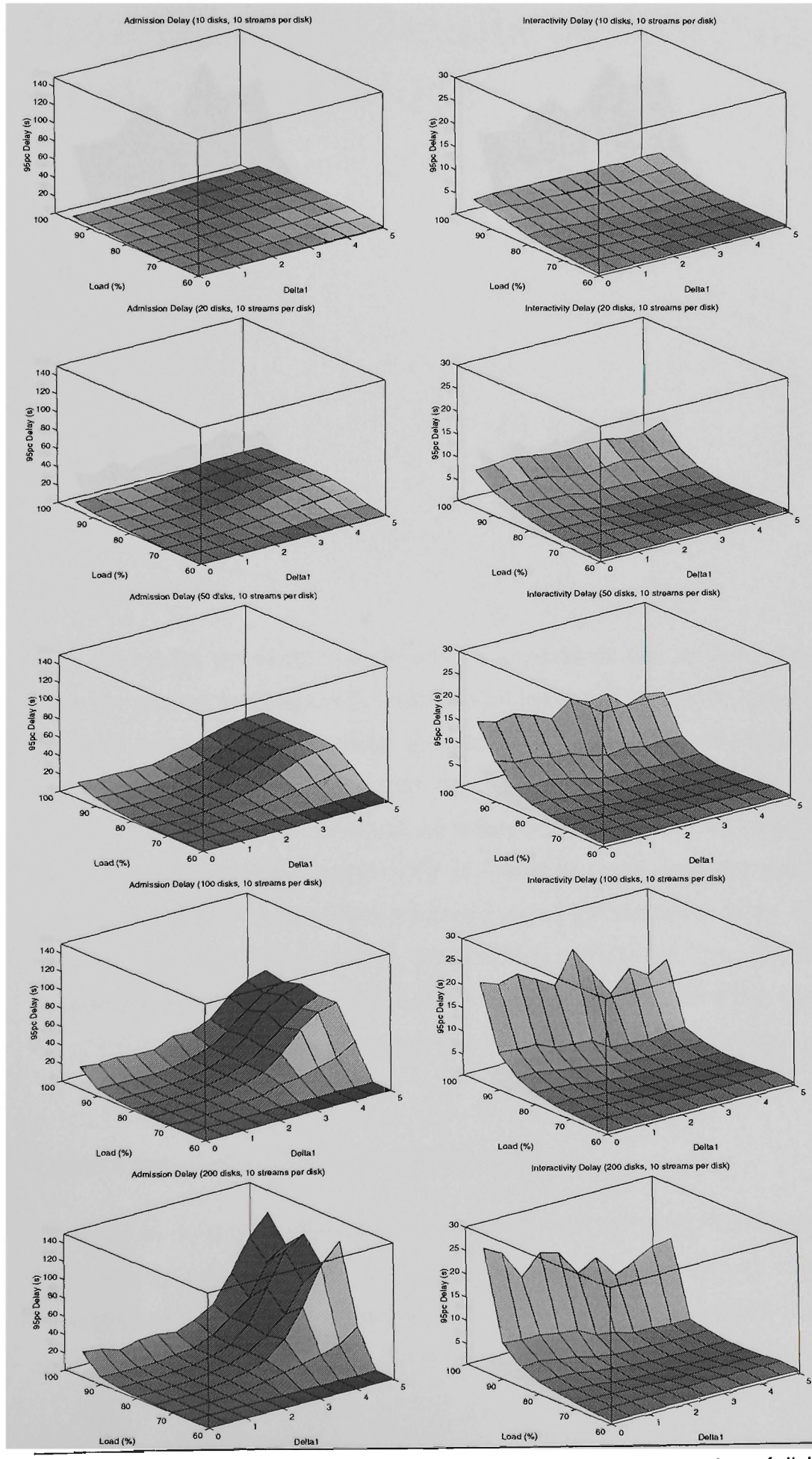

Figure B.4 95th percentile admission and interactivity delays vs number of disks

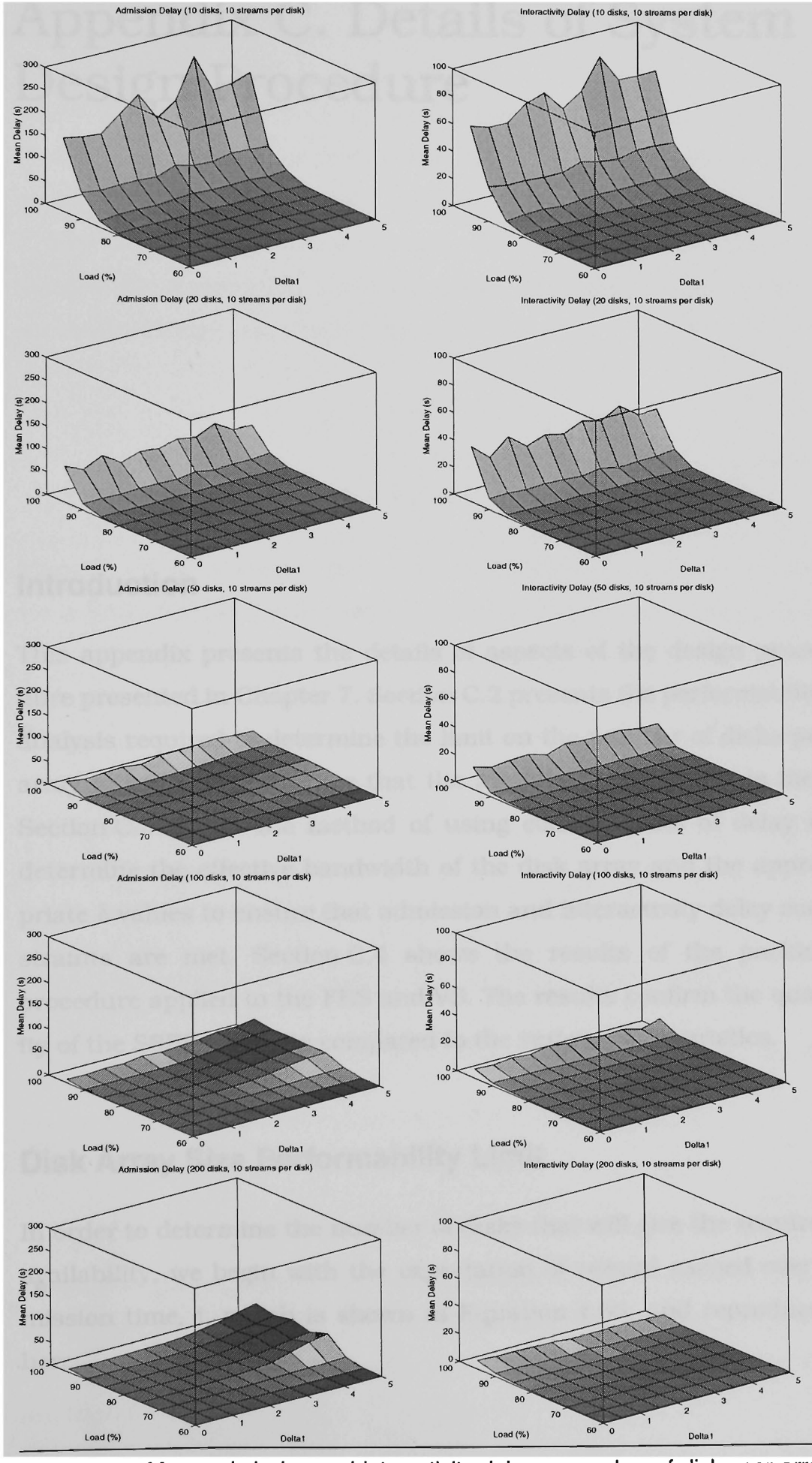

Figure B.5 Mean admission and interactivity delay vs number of disks per array for a system with no blocking

Appendix C. Details of System Design Procedure

C.1 Introduction

This appendix presents the details of aspects of the design procedure presented in Chapter 7. Section C.2 presents the performability analysis required to determine the limit on the number of disks per array in order to guarantee that the availability constraint is met. Section C.3 shows the method of using contour plots of delay to determine the effective bandwidth of the disk array and the appropriate δ values to ensure that admission and interactivity delay constraints are met. Section C.4 shows the results of the packing procedure applied to the FES and VS. The results confirm the quality of the SSBF heuristic compared to the various FF heuristics.

C.2 Disk Array Size Performability Limit

In order to determine the number of disks that will give the required availability, we begin with the expectation of reward earned over a mission time, t, which is shown in Equation 4.55, and reproduced here:

$$E[Y(t)] = \sum_{i=0}^{2} a_i \bar{r}_i t \qquad \text{(Eqn C.1)}$$

where a_i represents the steady-state probability of the array being in state i, $\bar{r}_i$ represents the reward earned per unit time while in state i and t represents elapsed time (mission time). Now, normalising the $\bar{r}_i$'s by dividing by $\bar{r}_0$, (the expected reward in state 0) and taking the value of the expectation of reward earned per unit time, we obtain a measure of long-term availability, A:

$$\begin{aligned} A &= \sum_{i=0}^{2} \frac{a_i \bar{r}_i}{\bar{r}_0} \\ &= a_0 + \frac{\bar{r}_1}{\bar{r}_0} a_1 \end{aligned} \qquad \text{(Eqn C.2)}$$

since $\bar{r}_2 = 0$ for a RAID 5 disk array. Now define $p = \frac{\bar{r}_1}{\bar{r}_0}$ as the penalty for a RAID 5 array being partially failed. p can assume a value from 0.5 to 1 dependent on the load variation with time of day. If, for example, load is constant at the peak load then p=0.5, since a RAID-5 can only serve 50% of peak capacity when partially failed. However if the array is almost always lightly loaded (less than 50%) then p will approach unity, since there will be no penalty for being in a partially failed state. For the viewers vs time of day statistics shown in Figure 4.7, p=0.765 and that is what is assumed here.

Substituting values of a_0 and a_1 into Equation C.2 we obtain:

$$A = \frac{\mu'(\mu + \lambda') + p\mu'\lambda}{\mu\mu' + \lambda\lambda' + \lambda'\mu' + \lambda\mu'} \qquad \text{(Eqn C.3)}$$

and substituting the definitions of λ and λ' this becomes:

$$A = \frac{\mu'(\mu + (D-1)\lambda_s) + p\mu' D\lambda_s}{\mu\mu' + D(D-1)\lambda_s^2 + (D-1)\lambda_s\mu' + D\lambda_s\mu'} \qquad \text{(Eqn C.4)}$$

By rearranging Equation C.4, we can obtain a solution for D to give a constraint on the number of disks in an array based on the required availability, disk reliability and repair times. Omitting the steps, the solution for D is:

$$D \le \left\lfloor \frac{-b + \sqrt{b^2 - 4ac}}{2a} \right\rfloor \quad \text{where} \quad \begin{aligned} a &= A\lambda_s^2 \\ b &= 2A\lambda_s\mu' - A\lambda_s^2 - \lambda_s\mu' - p\lambda_s\mu' \\ c &= \lambda_s\mu' + A\mu\mu' - \mu\mu' - A\lambda_s\mu' \end{aligned} \qquad \text{(Eqn C.5)}$$

C.3 Effective Bandwidth due to CAC

This section considers the problem of determining a maximum "effective bandwidth" for the disk array design in Chapter 7. The raw bandwidth of the array is 512 streams (served from 73 disks), but this may be required to be reduced to ensure that particular delay constraints are met. By taking horizontal slices through the graphs shown in Appendix B, contour plots can be developed which effectively show regions of feasible operation, given a particular delay constraint.

Consider the contour plots shown in Figure C.1. These plots show

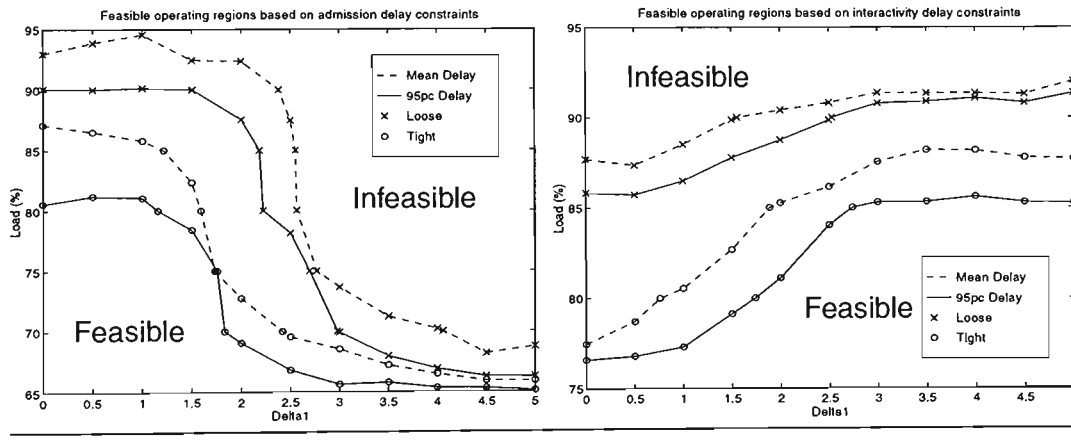

Figure C.1 Contour plots showing regions of feasible operation for admission and interactivity delay constraints.

the feasible operating regions of a disk array consisting of 70 disks (serving 10 streams per disk) for two different sets of delay constraints. For simplicity, the predictive CAC scheme used here it is assumed to have δ_2=0, although other values of δ_2 can be easily investigated. The constraints used in the loose and tight cases are shown in Table C.1. Note that the loose constraints correspond to the requirements in the design example in Chapter 7.

Table C.1 Constraints used for "loose" and "tight" contours in Figure C.1.

	Loose		Tight	
Constraint	Mean	95 pc	Mean	95 pc
Admission Delay (s)	2.5	5	1	2
Interactivity Delay (s)	1	3	0.5	1

From Figure C.1 it can be determined, for example, that to support a mean admission delay of 1 second the array can operate at a maximum utilisation of about 87% and that δ_1 should be set to 0. This setting will not, however, meet the 95pc constraint on admission delay or the "tight" interactivity constraints. In order to find the correct operating point it is necessary to overlay the required constraints onto a single graph, and find the point in the feasible region that allows the highest utilisation and select the corresponding value of δ_1.

Figure C.2 shows the most restrictive contours for both admission and interactivity delay constraints for the "loose" case considered above. The curves shown are for the 95th percentile constraints since Figure C.1 showed these to be stricter than the corresponding mean delay constraints. From the figure it can be seen that the highest feasible utilisation is about 88.3% and a value of $\delta_1 = 1.8$ will result in all the imposed delay constraints being met. Note that if the previous simple CAC schemes were used, the maximum possible server utilisation would be less than 86%, in this case. The figure of 88% is used in Chapter 7 to complete the design procedure.

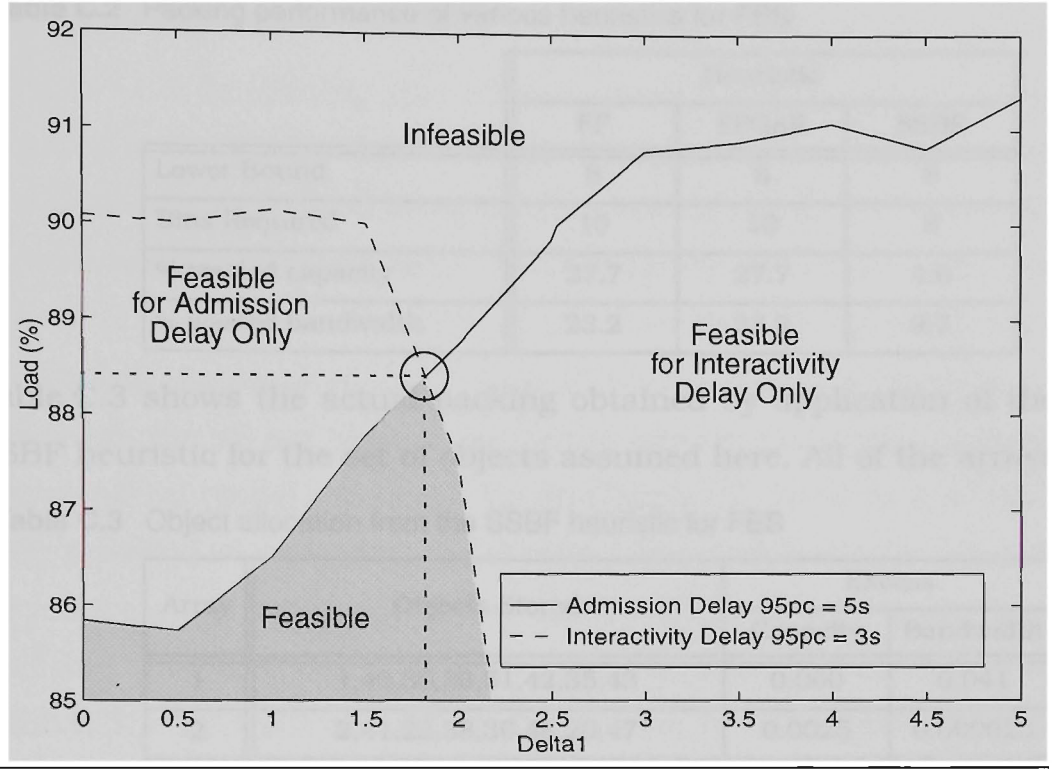

Figure C.2 Feasible regions for loose call admission and interactivity delay constraints

C.4 Object Packing

This section shows the results of the object packing used in the design example of Chapter 7 for the FES and VS.

C.4.1 FES Object Packing

Since the object packing heuristics are not perfect or predictable it is uncertain how many objects will actually fit on the 8 arrays specified as the lower bound for each FES in Section 7.8.1. The packing results of the FF, FFGAR and SSBF heuristics for this case are shown in Table C.2. Note that since the same number of bins were used by FF and FFGAR the total resources wasted are equal, despite the fact that the actual object placements are considerably different.

It is clear that SSBF provides the most efficient packing, meeting the lower bound of 8 bins (disk arrays) while the other two heuristics require an additional 2 arrays which significantly increases system cost.

Table C.2 Packing performance of various heuristics for FES

	Heuristic		
	FF	FFGAR	SSBF
Lower Bound	8	8	8
Bins Required	10	10	8
% wasted capacity	27.7	27.7	4.0
% wasted bandwidth	23.2	23.2	9.7

Table C.3 shows the actual packing obtained by application of the SSBF heuristic for the set of objects assumed here. All of the arrays

Table C.3 Object allocation from the SSBF heuristic for FES

Array	Objects Stored	Excess	
		Capacity	Bandwidth
1	1,40,30,33,51,42,35,43	0.060	0.041
2	2,41,22,38,36,48,20,47	0.0025	0.000023
3	3,19,50,34,44,32,45,25	0.047	0.027
4	4,26,39,37,52,31,46,29,53	0.023	0.060
5	5,28,16,49,24,55,11	0.10	0.017
6	6,17,57,15,54,10,58	0.14	0.28
7	7,14,27,59,23,60,9	0.14	0.04
8	8,56,21,18,13,12	0.31	0.05

are very well packed in both bandwidth and capacity dimensions, with the exception of array 8 which has 31% free capacity. This free capacity can be put to good use, however, storing additional movies (2 to 3 movies will fit) without any bandwidth allocated to them. The movies stored will be selected by the caching algorithm such that they are likely to become more popular in future. This way, when they do increase in popularity, a copy already resides locally and can be used to serve requests immediately, provided the overall load on the array will not exceed the limit of 450. This small amount of extra storage will help to ensure the efficient operation of the caching algorithms.

C.4.2 VS Object Packing

Section 7.8.2 determined that a minimum of 8 disk arrays would be required in the VS. To determine the actual number required, a set of representative objects must be allocated to the arrays using the appropriate packing heuristics. The popularity model to use in this case is of particular interest. Since the majority of the popular titles are held in the cache at the various FES's the requests which actually reach the VS are likely to be for the less popular titles. As such the empirical model used thus far (in Chapter 7) must be appropriately modified to represent this change. This modification is affected by reducing the popularity of the top 60 objects to zero[1] and renormalising the popularities of the remaining objects such that they total 1. The modified popularity distribution is still heavily skewed, although not nearly as steeply as the overall empirical distribution which includes the most popular 60 objects. Indeed, the popularity is now closely approximated by the Zipf distribution. The modified empirical popularity model is used for the packing considered here with 1000 objects to be packed. This accounts for the 60 objects in each of the FES caches by allocating them a very small bandwidth requirement.

The results of this packing process are shown in Table C.4 for the three heuristics considered in this thesis. SSBF is again seen to outperform the other two heuristics which both exceed the lower bound by 3 arrays (or 33%). Notice that the lower bound shown in the table is 9 arrays, whereas the lower bound found in Chapter 7 was only 8 arrays. The reason for this discrepancy is that the bandwidth requirement of the VS meant that exactly 8 arrays were required and the randomness introduced by selecting object bandwidths from an empirical distribution has increased this fractionally above 8, which of course must be rounded to the next highest integer, 9. This also

1. Note that these files will still need to be stored on the video server since the various FES's may be caching different objects at any time, but their bandwidth requirement should be very small.

accounts for the fact that SSBF has considerable wasted resources even though it achieves a packing which matches the lower bound. These wasted resources come about because only fractionally more that 8 arrays were required. This unused bandwidth and capacity can be used to store new videos as they are released or to store additional copies of the most popular titles to increase redundancy.

Table C.4 Packing performance of various heuristics for VS

	Heuristic		
	FF	FFGAR	SSBF
Lower Bound	9	9	9
Bins Required	12	12	9
% wasted capacity	36.9	36.9	15.8
% wasted bandwidth	33.4	33.4	11.1

It is impractical to show the allocation of all 1,000 objects in this case. The majority of the free space, however, is on the final array with 85% of the bandwidth and 99% of the capacity on this array available for use by other objects (new releases etc.). Clearly, this is preferable to having the unused resources spread in small sections across all arrays where it would remain wasted.